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Natural language acquisition and rhetoric

in artificial intelligence

by

Richard David Johnson

A Thesis Submitted to the

Graduate Faculty in Partial Fulfillment of the

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TABLE OF CONTENTS

INTRODUCTION

During the 1980s, artificial intelligence research started to undergo a quiet, but important shift in focus from research in computer science to research in the human sciences and humanities. Though in the past, artificial intelligence has primarily been researched by computer scientists, the need for input from the human sciences has invited a great amount of cross-disciplinary work by members of many different callings. Rarely do people start out in the field of artificial intelligence; rather, the dream of building an intelligent machine infects them as they see the parallels between their work and the projects being undertaken in artificial intelligence. Because artificial intelligence is, in essence, studying the qualities of humanness, few disciplines can avoid somehow being tied in.

Whereas this multi-disciplinary effort has its appeal due to the amount of interest and work it stimulates, it also causes problems for the traditional paradigm developed and held by the discipline of artificial intelligence. The difficulties arise as scholars and experts from other disciplines recognize similarities between their work and artificial intelligence but also notice the simple, fault-ridden assumptions traditionally held by artificial intelligence about human behavior and thought. Many researchers have brought their expert knowledge from other fields to artificial intelligence only to find that researchers in artificial intelligence prefer to operate on simplistic synthetic theories developed within the discipline. George Reeke and Gerald Edelman, two prominent neurobiologists, probably put it best with their assessment of artificial intelligence's work with psychology and the neurosciences:

> Artificial intelligence is a science that finds itself in somewhat the same epistemological position as Aristotleian dentistry. Aristotle stated that women have fewer teeth than men and attributed this characteristic to women's supposed lesser need, men being stronger and more choleric, but he never bothered to look in Mrs. Aristotle's mouth to verify his theory. Similarly, AI has developed as an almost entirely synthetic enterprise, quite isolated from the complementary, analytic study of the biology of natural intelligence represented by psychology and the neurosciences (Reeke and Edelman 1988).

Reeke and Edelman's conclusion is one similar to that made by numerous other researchers who have tried to provide guidance for artificial intelligence. Often, after spending time trying to help research, these scholars and experts walk away disillusioned by the tenacious desire of artificial intelligence researchers to cling to inadequate synthetic theories.

Nowhere is this problem of keeping deficient theories more evidenced than in artificial intelligence's research into natural language. Major linguistic researchers like John Searle and Noam Chomsky look on in disbelief at some of the erroneous assumptions held in artificial intelligence about natural language. Once in a while they might even point out the problems with the synthetic theories. But instead of seriously considering the criticisms of experts from other fields, artificial intelligence researchers all too often end up concluding that those experts must be wrong or that the points brought up are too sophisticated for current research. What is often _not_ realized in their defenses is that these experts from other fields are making their criticisms on an essentially fundamental level that _is_ very relevant to current research.

Researchers from the human sciences and humanities often find, as Reeke and Edelman noticed with relation to psychology and the neurosciences, that artificial intelligence as a discipline has somewhat isolated itself from large segments of research in natural language done by the human sciences and humanities.

There seems to be a willingness to listen for what is immediately useable, but often all that is brought away is the terms of the other disciplines and vague understandings of concepts that are soon distorted to fit the assumptions held before.

Artificial intelligence often resembles a bright young student with talent and ability but also a bad habit of ignoring the years of work done by his mentors. With seemingly endless energy and goals, he rushes blindly into projects with a 'do now, ask questions later' approach. After the few initial successes of his work, he makes bold predictions and claims for the future. But because he doesn't know the similar paths that have been followed before, his work starts to experience barriers due to his naivete. After struggling with the barriers, he crosses campus to see one of his mentors who "might" know something about the topic. Picking up a few concepts and a new group of terms from the mentor, the student rushes back to work, leaving his mentor saying, "This is that, but . . ." But the student never hears the "but" part.

Like the student, artificial intelligence in the past has had a tendency to extract information from other disciplines that it feels is necessary, but doesn't understand the conditions under which that information is used in those fields. With regards to natural language research, artificial intelligence researchers have extracted the present terms and concepts from linguistics and philosophy of language and thrown them around in their research; but their research often lacks an understanding of the important pragmatic and social aspects of language acquisition and usage that form an essential part of human discourse.

Now I might be a little too bold in saying it, but it seems as if artificial intelligence has started to mature. After coming up against endless roadblocks and traveling down blind alleys, the discipline in the last half-decade has begun to incorporate ideas from several different areas. Researchers have found that many of the problems that face artificial intelligence now have already been extensively researched and often overcome in associated fields. We even find established artificial intelligence researchers making whole crossovers to other disciplines, especially to psychology.

With this willingness to step out of isolation, the discipline has experienced a gradual shift in focus. Whereas in the past research had focused overwhelmingly on computer programming, now a significant amount of research is being done with and in the human sciences (e.g., linguistics, anthropology, neurobiology, and psychology). Appropriately artificial intelligence is also shifting more towards research in the humanities as philosophy and critical theory have made contributions to the questions of what humans, as models of intelligent behavior, accomplish with natural language. If a sustained trend, the future of artificial intelligence research will soon be focused heavily in the human sciences and humanities.

Artificial Intelligence . . . and Rhetoric?

First off, we need to dispel the myth that artificial intelligence has some direct link to computer science. Many artificial intelligence researchers (e.g., Margaret Boden and Patrick Winston) who have grown over-enamored by our silicon wonders go out of their way to stress the link between computers and artificial intelligence; but, historically and theoretically, no holy bond exists between these fields. In fact, as we will find out, the mindset in artificial intelligence that computers are necessary has restricted the growth of the discipline. Often researchers find very useful analogies from other disciplines, then try to squash them into the confining hardware of a computer.

To gain an objective view of the discipline, we must always remember that computers are nothing like human brains; so we have little reason to expect that they are the only other possible entity for artificial intelligence. Analogies between human brains and computers can often be misleading because they assume a natural connection between brain and computer. Currently, the only reason why computers and artificial intelligence are so closely associated is because computers have traditionally been used in research, nothing more.

The focus of this work will be on natural language acquisition and usage as it pertains to artificial intelligence. By considering the qualities of natural language, an important issue that we will take up in this text is whether computers provide a proper framework for natural language. Due to the formal hardware of computers, artificial intelligence has relied heavily on the formal approaches to language that a few theories in linguistics can provide. However, as the discipline shifts focus and moves beyond the restrictive paradigm forced by a reliance on computers, we find ourselves free to pursue natural language through different avenues. The real, not imagined, capabilities of computers are important considerations for our discussion.

Therefore, in this text we will approach the issue of natural language in artificial intelligence on a different angle by recognizing its pragmatic purposes in social groups. Instead of looking at how human beings put sentences together and interpret words as traditional research has done, we will consider the language-in-use aspect of natural language as an important part of its acquisition and usage. Through an understanding of how humans employ the conventions of natural language in their social environments, we can better understand what would be required of machines that have language capabilities.

Rhetoric provides direction in this area. As a discipline, rhetoric studies the pragmatic uses of natural language that artificial intelligence wants its machines to have. By considering the many parallels between rhetoric and artificial intelligence, this text will identify the qualities that a machine would need to use natural language rhetorically.

But before people start dusting off the works of Plato, Aristotle, Cicero, and Quintillian, a clarification needs to be made: Rhetoric like many other fields in the humanities can offer guidance as a mentor to natural language research in artificial intelligence, but extracting the terms and synthesizing concepts to fit a particular machine would be a naive mistake. As this text will attempt to do, drawing conclusions through considerations of rhetoric in artificial intelligence can provide insight into how intelligent machines can use natural language in social environments as humans do. However, restricting ourselves to a specific type of machine restricts our ability to understand what is needed for intelligence. In fact, the insights provided by rhetoric tend to guide us toward the proper type of machine needed for artificial intelligence rather than tell us how natural language can fit our current machines.

The Purpose of This Text

The purpose of this text is to build a bridge between established research in the humanities and research into artificial intelligence. The earlier sections of the text serve as an introduction to artificial intelligence in which the current issues and problems are discussed. The later sections move directly into issues that involve rhetoric and other disciplines from the humanities such as philosophy and socio-linguistics. The last two sections draw direct parallels between rhetoric and artificial intelligence that show what type of machine would be needed to act rhetorically. Therefore, the discussion won't be flooded with the technical language that makes a great majority of artificial intelligence research inaccessable to researchers outside of the discipline. With some luck, the bridge developed by this text will help other researchers from the humanities recognize where their work could be followed by artificial intelligence.

Already the bridges from psychology and linguistics are growing stronger; as the focus of artificial intelligence continues to shift toward the human sciences and humanities, these fields can take on a new importance to artificial intelligence research.

HISTORY AND DEFINITION

For the little more than three decades since research into artificial intelligence emerged from the science of cybernetics, researchers have stretched the label "artificial intelligence" to represent so many diverse areas of research that a clear definition of the discipline is difficult to determine. Due to the public's lack of knowledge about the field, researchers have been able to repeatedly identify their research with the financially advantageous label of "artificial intelligence" while not working toward its goal of a machine that thinks.

In this section we will discuss the changes in the discipline up until 1980 with special attention to issues of natural language usage. Through this historical context, we will look at what "traditional" artificial intelligence now holds up as the definition of "artificial intelligence" as compared to the original definition from the 1950s. And finally, to clear up ambiguities, this section will provide a clear definition of artificial intelligence that the rest of the text will follow.

A Historical Background of Artificial Research to 1980

In his book Cybernetics (1961), Norbert Weiner, the founder of cybernetic science, suggested that a possible practical application of cybernetic theory might allow scientists and engineers to develop machines that processed information similarly to human beings (Weiner 1961). Like Information Theory from which it emerged, cybernetics, as the science of communication and control in machine and animal, attempts to formalize all forms of communication into analytical constructs. In this way, researchers in cybernetics can apply analogous theories from statistical mechanics toward understanding the processes of communication in systems. Weiner felt that human communication processes could likewise be studied statistically and possibly applied to machine communication processes.

Though more a mere suggestion on Weiner's part than a serious consideration, scientists took to the idea with some enthusiasm. With the advent of the atomic age and the many other engineering feats during the Second World War, the world had come to expect the unbelievable from technology. Consequently, when Atanasoff and Berry, working at Iowa State University, announced the invention of the digital computer, it wasn't long before scientists and engineers started to envision their products of electronic technology as more than expensive adding machines. Taking their roots and support from the successful research in cybernetic science, by the middle 1950s two distinct branches of artificial intelligence emerged with high expectations.

The first branch, referred to as the "heuristic" branch in this text, found the newly invented digital computer to be a suitable framework in which human thought could be developed through proper programming. Recognizing digital computers as symbol manipulators, not just number manipulators, this branch felt that physical reality could be symbolically represented in the same way numbers were represented in the digital computer's binary framework. Allen Newell and Herbert Simon, leading researchers in this branch, set their belief down clearly as a hypothesis:

> The Physical Symbol System Hypothesis: A physical symbol system has the necessary and sufficient means for general intelligent action (Simon and Newell 1958).

Following of post-behaviorist communication theories like formal versions of Peirce and Morris' theories of signs, Weiner's cybernetics, and the groundwork theories in cognition, Newell and Simon viewed the manipulation of physical symbols in the brain and machine as the essential source for thought and understanding.

Through conceiving of the mind as a manipulator of mental signs, Newell and Simon hypothesized that a physical symbol system of sufficient size could be considered "intelligent." They justified their use of digital computers as frameworks for artificial intelligence by arguing that though the brain and the computer possess different structures, they share a common bond as symbol manipulators. According to their hypothesis, by using programs to manipulate physical symbols through heuristics, the digital computer would be accomplishing an intelligent act similar to that accomplished by the human brain. Therefore, Newell and Simon argued, at an abstract level by manipulating physical symbols through formal rules, the brain and computer were indeed accomplishing the same tasks through different physical structures (Simon and Newell 1958, Newell and Simon 1983).

The second branch, referred to as the "connectionist" branch in this text, spurned the temptation to use the computer as a framework and instead chose to approach the development of artificial intelligence by modeling the brain through the use of artificial "neurons." Inspired by the newly established field of neuroscience and recognizing the inherent complexity in formalizing intelligent processes, Frank Rosenblatt argued that developing and "training" an artificial brain would eliminate the need for programmed formal rules (Rosenblatt 1962).

Through recent discoveries in neuroscience that biological neurons were stimulated in groups by patterns they recognized, he hypothesized that a network of artificial neurons could likewise be "taught" to recognize patterns. In essence, these networks would "learn" and respond to past experiences with recognized patterns; meanwhile, new experiences would be placed into the machine's memory by stimulating different groups of neurons. This approach avoided the difficult problems brought up by a necessity to formalize the procedures of the brain:

> Many of the models . . . are concerned with the question of what logical structure a system must have if it is to exhibit some property, X . . . An alternative way of looking at the question is: what kind of system can evolve property X? I think we can show in a number of interesting cases that the second question can be solved without having an answer to the first.
>
> . . . it is both easier and more profitable to axiomatize the physical system and then investigate this system analytically to determine

> its behavior, than to axiomatize the behavior and then design a physical system by techniques of logical synthesis, which will in fact illuminate the functioning of the brain . . . that is to say, we can slate the types of systems which will evolve certain properties of interest without being able to say precisely what are the necessary organizational constraints in our finished system once it has completed its evolutionary process (Rosenblatt 1962).

Sidestepping the problem of determining the formal rules supposedly followed by the brain, Rosenblatt advocated allowing the artificial brain to develop its own intellectual structure by allowing it to experience the patterns in the world around it. The connectionist machine would have the ability to "self-organize" information within its framework. Using this theoretical basis, Rosenblatt began developing what he called "perceptrons," networks of artificial neurons. Perceptrons were networks of analog electronic devices connected in parallel that were stimulated through sensors attached to the machine.

Probably surprising the scientific community, by the late 1950s both research branches were claiming success and making bold predictions for the future. Having developed programs in digital computers that could use heuristics from deductive logic to prove theorems in propositional calculus, Newell and Simon enthusiastically wrote in 1958:

> We now have the elements of a theory of heuristic (as contrasted with algorithmic) problem solving; and we can use this theory both to understand human heuristic processes and to simulate such processes with digital computers. Intuition, insight, and learning are no longer exclusive possessions of humans: any large high-speed computer can be programmed to exhibit them also (Simon and Newell 1958).

Meanwhile, having taught a perceptron to recognize, classify, and separate similar patterns from dissimilar patterns, Rosenblatt wrote proudly in 1958:

> For the first time, we have a machine which is capable of having original ideas. As an analogue of the biological brain, the perceptron, more precisely, the theory of statistical separability, seems to come closer to meeting the requirements of a functional explanation . . . As concept, it would seem that the perceptron has established, beyond doubt, the feasibility and principle of non-human systems which may embody human cognitive functions (Rosenblatt 1958).

However, despite the predictions and high expectations, both branches soon ran into a problem that has plagued artificial intelligence research ever since, "combinitorial explosion." Combinatorial explosion occurs when the machine goes beyond simple puzzles and attempts to solve complex real-world problems. Though both branches had proven the ability to solve simple problems, attempts to upscale their machines to handle more multifaceted situations would cause the computational needs of each system to grow exponentially instead of geometrically--or to put it more dramatically, the needs "exploded" (Rumelhart et al. 1986).

Though the heuristic branch using computers could point to their machines' abilities to play checkers, real-world complexities such as natural language usage were clearly beyond the machines' capabilities. Likewise, though perceptrons had shown an ability to recognize simple patterns, their application to anything above that level was hampered by the sluggishness and inefficiency of their hardware.

Competition and the death of connectionism

The problems with combinatorial explosion quickly bogged down both branches. With the realization of a much larger problem than either branch had first anticipated, the middle 1960s brought on a sense of heavy competition as both approaches strived for recognition and government funding. With the enthusiastic claims made by artificial intelligence researchers in both branches, the Defense Department's Advanced Research Progects Agency (DARPA), as the primary source of funding for both branches, began expecting applicable results from the money it had invested (Papert 1988). But neither approach could hold up any results with real-world applications. With the Vietnam war approaching, playing checkers wasn't seen as an advantage worth using research funds.

In 1969, Marvin Minsky and Seymour Papert, researching symbol manipulation on digital computers at MIT, published Perceptrons: An Introduction to Computational Geometry. In the book, they analyzed their competititors' research into neural nets and artificial brains and concluded:

> The results of these hundreds of projects and experiments were generally disappointing, and the expectations inconclusive. The machines usually work quite well on very simple problems but deteriorate very rapidly as the tasks assigned to them get harder (Minsky and Papert 1969).

Though the same could be said about heuristic artificial intelligence at the time, Minsky and Papert argued effectively from philosophical and technological perspectives that connectionist theory was misguided and infeasible (Dreyfus and Dreyfus 1988). In a research field competing for recognition and money from a naive government, their arguments against perceptrons gained great influence--more than even they probably anticipated.

Unable to defend itself from Minsky and Papert's allegations that perceptrons would never go beyond simple pattern recognition problems, the connectionist approach found its funding drying up and being diverted into research using digital computers. By the early 1970s, research into connectionist theory had all but ended, and symbol manipulating became the undisputed flag bearer for artificial intelligence.

David Rumelhart and James McClelland wrote:

> Minsky and Papert's analysis of the limitations of the one-layer perceptron, coupled with some of the early successes of the symbolic processing approach in artificial intelligence, was enough to suggest to a large number of workers in the field that there was no future in perceptron-like computational devices for artificial intelligence and cognitive psychology (Rumelhart et al. 1986).

Stagnation in heuristic artificial intelligence

Despite their surprisingly easy victory over connectionist theory, the researchers in physical symbol manipulation still could not resolve their own problems with combinatorial explosion. As computer hardware improved, however, computers could work faster with much more data. A few ambitious researchers like Terry Winograd started attempting to program formalized syntactic features of natural language into their digital computers to manipulate words. Following the lead offered by Chomsky's theories of syntax, Winograd felt that "many of these (syntactic) rules could be formulated in a precise way within a framework of mathematical computation theory" (Winograd 1976). However, even though they limited themselves to syntax, extrapolating their work into real language use by the machine required incredible computing power that dwarfed even their strongest computers.

Also, Rosenblatt's observation, that formalizing the processes of human reasoning into heuristics would be very difficult, started to materialize as researchers like Winograd tried to program natural language into computers (Winograd and Flores 1986). Unlike checkers, chess, or other systems where the rules were well defined, natural language proved to be fluid-like and difficult to formalize. Their support in linguistics also started to erode. Trying to find such formal rules in language, linguists had concentrated on syntax alone, believing that theories incorporating semantics and pragmatics would be built up later around the syntactic hub. However, the works of Grice (1983) and Searle (1969) reinforced the importance of linguistic considerations of meaning to syntactic competence. Winograd recognized this dilemma when he wrote:

> The computational mechanisms developed for theories of syntax are not adequate for larger questions of meaning and the structure of discourse (Winograd 1976).

The heuristic branch's inability to answer questions of syntax, no less meaning, caused research to slow down considerably. Recognizing the extreme complexity of natural language use, heuristic artificial intelligence backed off from attempting to achieve language use as a whole. Heuristic researchers started to focus solely on developing machines that showed syntactic competence. The common belief with a taste of behaviorism was that if a computer can outwardly mimic a thinking human, whether it was actually thinking <u>as</u> a human or not was irrelevant (Rapaport 1988).

Heuristic researchers had given up the goal of developing a thinking machine in favor of a machine that appears to simulate human thought. This change in goals represented a significant change on their parts in the definition of artificial intelligence. With their new definition, heuristic researchers started to view intelligence as an act outside the machine for perceivers to determine, rather than an internal intellectual phenomena.

Definitions of Artificial Intelligence

As said earlier, a clear definition of the term "artificial intelligence" is non-existent. Researchers in the heuristic branch conceive of artificial intelligence quite differently than connectionists do. This ambiguity causes fundamental misunderstandings in the public about what exactly artificial intelligence research is trying to accomplish. To most people unfamiliar with the field, artificial intelligence is "that thing computer scientists are trying to develop." When engineers claim that their machines use "artificial intelligence," people start to wonder when these robots and such will start taking over the world as superior creatures to humans. And it doesn't help to have heuristic researchers like Marvin Minsky parading around claiming that "we'll be lucky if the next generation of computers will keep us around as pets" (Searle 1984).

In truth, artificial intelligence, the heuristic branch particularly, thrives on the public's misconception of what researchers in this field are actually doing. Its label has been stretched over so many diverse areas of research that "artificial intelligence" means nothing specific (Reeke and Edelman 1988). And most artificial intelligence researchers indirectly promote the public's misconceptions by not clarifying their work. Hardly do the words "artificial intelligence" escape from their mouths before government and corporate funds start filling their budgets. Undeniably, a financial benefit exists if researchers can somehow slip their projects into this field.

Therefore, in this section, we will clarify the many meanings of "artificial intelligence" by looking at what the field of artificial intelligence is trying accomplish. Then, we will set down a new, actually an old, definition of artificial intelligence that will be used for this text.

The altered definition of artificial intelligence

Some people like to refer to heuristic artificial intelligence as the "traditional branch." This designation exists because since the middle 1960s, the heuristic branch has dominated the field of artificial intelligence. Even now, a great majority of the work done under the label of "artificial intelligence" is from the heuristic branch. So when we hear about machines that exhibit "artificial intelligence," generally what is meant is heuristic artificial intelligence.

Marvin Minsky probably speaks for most of the heuristic branch when he defines an artificially intelligent machine as:

> A machine is artificially intelligent when it has the capabilities to do something that if done by a human would be considered intelligent (Minsky 1986).

In his influencial book, Artificial Intelligence, Patrick Winston defined artificial intelligence as:

> The study of ideas that enable computers to be intelligent (Winston 1984).

Rather clearly, these present day definitions of heuristic artificial intelligence represent a shift away from Newell and Simon's conception of artificial intelligence. To them, thought was achieved through the manipulation of symbols. Under their conception of human reasoning and thought the digital computer and the brain were considered compatible media for thought. These pioneers felt that formalization of human thought and reasoning would provide the main challenge to achieving a thinking machine. A formidable task, they believed, but an achievable one. Simon and Newell claimed quite boldly that by 1968, a digital computer will:

> --be the world's chess champion.
> --discover and prove an important new mathematical theorem.
> --write music that will be accepted by critics as possessing considerable aesthetic value.
> --cause most theories in psychology to take the form of computer programs, or of qualitative statements about the characteristics of computer programs (Simon and Newell 1958).

It is quite clear that the pioneers in heuristic artificial intelligence believed that a computer could indeed <u>achieve</u> human intelligence, not just "do something that if done by a human would be considered intelligent."

However, in present day heuristic artificial intelligence, we find that heuristic researchers no longer claim to be developing human thought in a machine. Instead, heuristic researchers have broken their definition of artificial intelligence into two parts, calling one pursuit "weak" artificial intelligence and the other "strong" artificial intelligence. Weak artificial intelligence is defined by Minsky's conception that a machine doing something that would be considered "intelligent" if done by a human shows artificial intelligence. Strong artificial intelligence is what Newell, Simon, Rosenblatt and most people outside of the heuristic branch conceive of as artificial intelligence--a machine that possesses thought.

Classifying artificial intelligence as "weak" and "strong" is somewhat deceptive. In weak artificial intelligence researchers are attempting to program computers to outwardly seem intelligent--to simulate human thought. Strong artificial intelligence, which no one in the heuristic branch is researching, is when a machine actually thinks as a human. Weak assumes the perception of intelligence by an outside source; strong assumes the actual existence of this intelligence within the machine.

These conceptions of what artificial intelligence means are very different. However, the designation of weak/strong suggests that the two are similar. Heuristic researchers would have others believe that once they achieve weak artificial intelligence, it will only be a small step to further develop strong artificial intelligence. Later in this text, we will show that this is not the case.

This text's definition of artificial intelligence

So what is the definition of "artificial intelligence?" Newell, Simon, and Rosenblatt as pioneers in the field felt that artificial intelligence was a machine's attainment of human thought. To clear up ambiguities and misconceptions, we need to re-establish an honest, direct definition of artificial intelligence that can define the discipline--no "weaks," no "strongs." Anything else that cannot conform to the definition of artificial intelligence shouldn't be classified as such.

Newell, Simon, and Rosenblatt had the best conception of what artificial intelligence actually means. They fully believed in and pursued the possibility of a machine that thinks as a human. Their original goal represents the most straightforward concept of what we should expect from artificial intelligence research. Therefore, for this text, we will revert to their original definition of artificial intelligence.

> Definition: Artificial Intelligence exists when a machine thinks as a human.

As in many other complex disciplines, the definition is simple, but flexible. Unlike the altered definitions used in the heuristic branch, no qualifiers are needed to direct which way this definition can be used; 'machine' does not imply 'computer' and 'as' does not mean 'like' or 'simulate.' Finally, 'thinks as a human' points out that we should use our best research into human thought processes to determine the definition of 'intelligence.'

Conclusion

Of course, many researchers will point out that we cannot jump right into developing machines that possess thought just because of a definition--much preliminary research needs to be done into both machines and the human brain. This is true. However, as in any scientific discipline, research should be able to extend itself through philosophy to show us why someday it might lead to its goals. Likewise, artificial intelligence should be able to provide a theoretical basis for believing it is in the right direction.

In the next section of this text, we will be analyzing the philosophy behind present heuristic artificial intelligence research. The background information and definition in this section will provide a measuring stick against which we can measure the possibilities of success of natural language acquisition and usage by machines.

NATURAL LANGUAGE AND HEURISTICS

When asked whether machines could ever achieve artificial intelligence, Alan Turing, one of the first major figures in computer science, avoided answering the question directly by proposing a test that he felt would prove whether a machine could be considered "artificially intelligent." His test, the "Imitation Game" soon became the standard against which artificial intelligence measured itself.

In the Imitation Game, Turing set up the following scenario: Allow two human beings and a machine to communicate freely through some medium that would not give away their identities. The humans and machine would then correspond amongst themselves with two intents: First, the humans would attempt to determine which one of the other two is the machine and which is the human; second, all three would attempt to convince the other two that they are human and not the machine. A machine could be considered "artificially intelligent" if it could consistently persuade each human that it, the machine, is the other human (Turing 1950).

Despite the claim sometimes found in the popular media that a computer is acting "artificially intelligent," the machines developed by artificial intelligence research have yet to pass the requirements of the Imitation Game. But the Imitation Game has provided a rather durable test against which theoretical models of artificial intelligence are tested. Unfortunately, it also has provided a multitude of different opinions as to what a machine would require to be considered intelligent. Since language usage represents one of the most obvious and important aspects of intelligence, most of these controversies center on the issue of machines using natural language. Invariably, natural language has been the primary barrier to success in artificial intelligence.

The 1980s was a decade of re-evaluation for the heuristic branch as theorists and researchers sorted through the diverse opinions over the place and importance of natural language in artificial intelligence. As we start into the 1990s due to the barriers provided by natural language acquisition and usage, the theoretical position of heuristic artificial intelligence is more defined, but far narrower than that of only a decade ago. This section will discuss the contemporary theoretical approach of the heuristic branch to natural language acquisition and usage in artificial intelligence and provide the reasoning behind its current assumptions.

Syntax and Referents

Taking Turing's imitation game at its surface, heuristic researchers have generally interpreted the game as showing that artificial intelligence primarily requires the outward simulation of thought by the machine. As a result, issues in natural language acquistion and usage have become the focal consideration in the heuristic branch as researchers attempt to program the outward appearances of human intelligence into a computer. Whether or not computers actually understand the meaning behind natural language usage is seen as less a concern than the proper outward use of the language symbols. Most heuristic researchers believe that language competence to persuade or "fool" the humans into believing the machine thinks is the most important feature of an artificially intelligent machine (Rapaport 1988).

Assuming human mental processes to be formally cognitive and deterministic, the heuristic branch's goal is to formalize the activities of humans into heuristics so that the computer can simulate cognitive abilities (Schank 1986). Likewise with natural language, they feel that language processes can be formalized into common syntactic structures that computers can use to interpret and respond to inputted sentences.

For this reason, current heuristic artificial intelligence inquiry into natural language focuses mainly on issues of syntactic competence. Though many researchers claim to be working with word meanings, their formal systems for semantics usually represent limited support systems for the syntactic processes of their computers. This focus on the outward simulation of natural language use results from two major limitations to heuristic artificial intelligence: first, as we will discuss later, the computer has a formal framework that can only accept determined constants; second, research into semantics by linguistics and the philosophy of language, though very successful theoretically, hasn't provided a clear picture of how semantics can by formalized for a computer. So in their desire to start programming, heuristic researchers have accepted formal views of linguistics with their own synthetic concepts of formalized semantics.

We can see the development of the heuristic branch's current theories toward natural language as progressive attempts to further accommodate for semantics through considerations of syntax. The first researchers focused on keyword search programs that had almost no attempts to gain a sense of meaning of words. A good example of this approach was Weizenbaum's ELIZA program (Weizenbaum 1966, 1967) Here is a small transcript of a conversation with ELIZA:

User: Men are all alike.
ELIZA: In what way?
User: They're always bugging us about something or other.
ELIZA: Can you think of a specific example?
User: Well, my boyfriend made me come here.
ELIZA: Your boyfriend made you come here.
User: He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.

The program works through a simple process to make its responses. It uses either stock phrases like "In what way?" or it inserts sentence fragments from the user's previous sentence into programmed response patterns. Working through these syntactic patterns, the computer itself really has no concept of meaning, though at times its use of language might give the impression that it does (Ritchie and Thompson 1983).

The limitations of programs like ELIZA to make meaning connections with words led researchers in the early 1970s to look into ways to develop limited semantic qualities within the computer software. The common approach was to use formalized semantic referents to equate and define each symbol with a set of semantic qualities. A good example of this approach is Winograd's SHRDLU program in which the computer could converse with a human about a simple system called "BLOCKS world" (Winograd 1972, 1976). Here is an example of a conversation with SHRDLU in BLOCKS world:

> User: pick up a red block.
> SHRDLU: OK
> User: grasp the pyramid.
> SHRDLU: I dont understand which pyramid you mean.
> User: what does the box contain.
> SHRDLU: The blue pyramid and the blue block.
> User: what is the pyramid supported by?
> SHRDLU: The box.

The computer can identify different entities through binary referents. For example, the red block might have the following features: [+ red], [+ flat top]; while the blue pyramid would have different features: [- red], [- flat top]. Corresponding to these features would be rules such as an entity can be placed on a [+ flat top], but an entity cannot be placed on a [- flat top].

To his credit, Winograd was the first to point out the severe limitations of SHRDLU, but he and many others saw it as a step toward semantics. At the time, when most computer programs focused on parsing routines to identify the grammatical structure of sentences, SHRDLU through its synthetic semantic referents did to a certain extent have a crude sense of meaning. By breaking meaning down into formal referents, the simplistic features and rules of the entities of "BLOCKS world" could be defined and programmed into computer frameworks. Terry Winograd in 1976 recognized the need for considerations of semantics by identifying the same shift away from syntax-based paradigms in linguistics when he wrote:

> Much of the early successes of this approach was based on a narrow concentration on problems of syntax, avoiding issues of meaning and communications in language use. From a commonsense point of view, communication and meaning are much more central to a theory of language than the details of word ordering. But paradoxically, this centricity makes them harder to attack theoretically. They are so intertwined with our basic ability to think and reason that it becomes impossible to talk about them as a separate field of study. In order to avoid this, linguists concentrated on syntax alone, and believed that more comprehensive theories could be built later around the syntactic core.
>
> There is much current dissatisfaction with this restrictive paradigm, and many prominent linguists are beginning to reject a syntax-dominated approach and to look at these broader issues (Winograd 1976).

At the time, Winograd felt that heuristic artificial intelligence would provide a valuable tool for this new emphasis on semantics in linguistics.

Heuristic Frames and Scripts

These attempts lead us to the present direction of research in heuristic artificial intelligence. Many programs like SHRDLU were built with meaning referents, but attempts to extend these programs beyond simple environments like BLOCKS world met again with the problems of combinatorial explosion in two forms:

1. Whereas SHRDLU used simple, predictable sentence structures, linguists had found the sentence structures used by humans to be more complex than first anticipated by generative grammar theories. Due to this complexity, computers struggled to analyze the many variations in human sentence use.

2. Entities, more complex than Winograd's hypothetical ones, needed extensive definitions through referents. A hypothetical block could be formalized into simple referents, but real-world entities needed extensive referential definitions to distinguish themselves from other entities (e.g. the differences between two like items such as two different humans.)

But a third, more important problem surfaced. Whether or not they could manipulate the language or even give words some sense of meaning, these computers were not doing anything that humans do. They represented silicon slaves that would pull apart instructions from a user and accomplish a hypothetical task. Obviously, human beings do more with natural language than just follow orders in an order-action, stimulous-response fashion. Unlike humans who possess intentional behavior, computer programs like SHRDLU could not act pragmatically.

For this reason, present heuristic artificial intelligence follows synthetic theories that attempt to formalize behavior processes and natural language into formal systems that try to accommodate aspects of syntax, semantics, and pragmatics.

Followed in different forms, Marvin Minsky's concept of "frames" in human behavior and natural language is still the motivating theoretical approach for the heuristic branch (Minsky 1986). Minsky, following work in cognitive science, hypothesizes that humans only need to reference certain categories of information in different situations. By referencing stored information in chunks of relevant material, the computer, he argues, can avoid combinational explosion by limiting its information set to what is needed in the present situation. Therefore, computers cut down on their needed computations considerably because they don't need to search through their entire data bases.

Taking this concept of frames one step further, Schank and Abelson added a formal sense of timed sequence to the use of frames (Schank and Abelson 1977, Schank 1986). They hypothesized that humans follow heuristics of behavior, referencing material based on the present point in a relevant behavior heuristic. By trying to understand human behavior, they hoped to draw the focus of the heuristic branch away from the complexities of syntactic sentence manipulations toward understandings of semantics and pragmatics. Schank and Abelson's best example of a script is that of the restaurant script:

> Consider, for example, the following situation. Imagine that you are hungry and that someone suggests a marvelous restaurant to you called Burger King. You happily go to this restaurant, armed as you always are, with a set of expectations about what will happen there. Specifically, you expect that you will: **ENTER; BE SEATED; GET & READ MENU; ORDER; BE SERVED; PAY;** and **EXIT**.
>
> Each of the bold faced "scenes" represent expectations of their own and are handled through their individual scripts (Schank 1986).

Since Schank and Abelson's hypothesis, frames, scripts and their counterparts have represented the main theoretical approach in heuristic artificial intelligence. The heuristic branch believes that human behavior and natural language, understood as scripts, can be codifiable into heuristics for programming into a computer. With a large grouping of these scripts and a large data base, the computer, they feel, can act and speak like a human being.

Ideally, when a question or statement is posed to the computer, it would find the "task environment," that serves the particular input, "search" among alternative courses of action in its database, and make a "choice" that best achieves the desired goals (Winograd and Flores 1986). To accommodate for semantic issues, Schank hypothesized that meaning can be broken down into "primitives" in much the same way that SHRDLU used referents. Except in his understanding of semantics, Schank argued that only a small set of primitive elements are needed to build up meaning of all concepts in natural language (Schank 1975). Therefore, meaning could be simplified into basic "actions" that can be used as descriptions of items in categories.

Schank points to the success of the frame/script approach in the form of computer programs that ask questions about a news event. Here is a transcript of a question-answer encounter with a program called CYRUS (the computer asks the questions and Schank provides the answers):

Initial User Question: Has Vance's wife ever met Mrs. Begin?

Q1: Did your wife ever meet Mrs. Begin?
  Q2: Where would they have met?
    Q3: Under what circumstances do diplomat's wives meet?
      Q4: Under what circumstances do diplomats meet?
      A4: On state visits to each other's countries. At international conferences.
    A3: When they accompany their husband's on these visits.
    Q3a: When did Vance go to Isreal?
    Q3b: When did Begin go to the U. S.?
    A3a/A3b: various dates can now be retrieved from memory
    Q3c: Did their wives accompany them on any of these trips?
    A3c: a trip where this happened is found
  Q2a: During what part of a trip would wives meet?
  A2a: during a state dinner

Final Revised Question: Was there a state dinner on May 24, 1977 during the diplomatic visit that Vance made to Isreal with his wife?

Answer (A1): Probably on May 24, 1977, in Jerusalem at a state dinner in which they were both present.

CYRUS' answer to initial question: YES, MOST RECENTLY AT A STATE DINNER IN ISREAL IN JAN 1980. (Schank 1986).

With limited consideration of their own theoretical basis, this program CYRUS, which represents one of the more advanced language using products of the heuristic branch, suffers from limitations that have troubled other heuristic approaches in the past. These types of programs still act in severely limited environments through stereotyped versions of what humans actually do.

Let's consider Schank's "restaurant script" for a moment. Those of us who have been to Burger King (the restaurant in his example) know well that this particular script would leave a computer sitting at a table hopelessly expecting a menu to be brought to it. Schank argues that the computer can mark the places where the script fails for future reference and ideally develop new scripts based on the new experience. Of course, the programmer could provide a special script for restaurants like Burger King (and McDonald's, Maid Rite, and White Castle) also, but the amount of scripts needed to handle the situations humans normally face would be enormous. Just the computation power needed to anticipate and accomplish even the most basic of human actions (like eating at a restaurant) invariably dwarfs the strongest, most expensive computers.

Searle's Chinese Room Argument

Of course, there have always been critics of artificial intelligence. Norbert Weiner and Alan Turing were among the first critics of the field when they asked whether we should even want thinking machines. But criticism in the 1980s and 1990s has become more specific than moralistic, being most relevant and most damning for the heuristic branch. Instead of asking how computers can achieve thought, we find most criticism arguing effectively that they will never achieve thought.

Until the 1980s, heuristic artificial intelligence researchers had no qualms about accepting the claim that they were working toward the ultimate goal of "strong artificial intelligence," the development of a "mind" in computers. Hubert Dreyfus, a philosopher, made some provoking arguments against heuristic artificial intelligence in his book What Computers Can't Do (1979). If anything, though, heuristic researchers realized that philosophers were a threat and started to ignore them as much as possible. The goal of a cognitive computer seemed to be further in the distance than originally anticipated, but they always assumed that they were on the right track. The designations of "weak" and "strong" were seen more as the two ends of a spectrum that would allow them to apply their research in "weak" artificial intelligence to future research in "strong" artificial intelligence. However, the distinctions between the two approaches have since grown further apart, leaving two separate camps. In the minds of heuristic researchers, "strong artificial intelligence" is more a case of distant future research than an immediate extension of their work.

This withdrawal into the confines of "weak" artificial intelligence was primarily due to a re-evaluation of the goals of artificial intelligence and a recognition of the limitations of the computer during the 1980s. Until then, critics of artificial intelligence had mainly centered on questions of whether a computer could encompass human qualities like love, empathy for humans, and human nature. But in 1980, John Searle, a speech acts theorist, delivered a scathing attack on the belief that computers could be programmed to "think." He viewed the heuristic branch's focus on outwardly simulating human thought as a return to behaviorism, since it claimed (as in its interpretation of Turing's Imitation Game) that the apprearance of intelligence means something <u>is</u>

intelligent (Searle 1984). His argument centered on a thought experiment he had devised called the Chinese Room Argument:

> Minds are semantical, in the sense that they have more than a formal structure, they have a content....
>
> Imagine that you are locked in a room, and in this room are several baskets full of Chinese symbols. Imagine that you (like me) do not understand a word of Chinese, but that you are given a rule book in English for manipulating these Chinese symbols. The rules specify the manipulations of the symbols purely formally, in terms of their syntax, not their semantics. So the rule might say: 'Take a squiggle-squiggle sign out of basket number one and put it next to a squoggle-squoggle sign from basket number two.' Now suppose that some other Chinese symbols are passed into the room, and that you are given further rules for passing back Chinese symbols out of the room. Suppose that unknown to you the symbols passed into the room are called 'questions' by the people outside the room, and the symbols you pass back out of the room are called 'answers to questions.' Suppose, furthermore, that the programmers are so good at designing the programs and that you are so good at manipulating the symbols, that very soon your answers are indistinguishable from those of a native Chinese speaker. There you are locked in your room shuffling your Chinese symbols and passing out Chinese symbols in response to incoming Chinese symbols. On the basis of the situation as I have described it, there is no way you could learn any Chinese simply by manipulating these formal symbols.
>
> Now the point of the story is simply this: by virtue of implementing a formal computer program from the point of view of an outside observer, you behave exactly as if you understand Chinese, but all the same you don't understand a word of Chinese (Searle 1984).

Searle's conclusion from his Chinese Room argument is that the formal systems which computers need are insufficient for the real semantic understanding that humans possess. Whereas the programmers of formal systems through scripts prescribe limited "meanings" for words through referents and primitives, humans actually experience the real meaning behind the words in the real world. Therefore, he argues, since computers cannot overcome their syntactic frameworks, they will never <u>understand</u> natural language and cannot become minds (Searle 1984).

Searle had effectively questioned the synthetic theories of syntax, semantics, and pragmatics held by the heuristic branch and reduced them back to modified theories of symbol manipulation. Meaning in formal systems used by computers was merely a product of other meaningless symbols put together into chunks as a definition. The Chinese Room Argument was a direct response to Schank and Abelson's conception that the mind worked with scripts that could be formalized.

As Searle points out, computers are symbol dependent machines that don't and can't have any understanding of the symbols they manipulate. Their restriction to symbol manipulation arises because the hardware of computers forces them to operate by moving meaningless charges through a formal framework. A word with a set of referents as defining characteristics for an entity doesn't give it a real sense of meaning, because the referents represent syntactic constructions themselves.

Schank did anticipate this problem of the difference between formal system meaning and semantic meaning. His adaptation of the theory of "primitive" elements of meaning is one in which a few certain actions are basic to reality and can be used to explain all concepts (Schank 1975). At these points, if his theory was correct, meaning and symbol in mind and computer has a determined essence. Therefore, identifying these primitives and building all word meanings on them would allow the machine to make a direct connection between symbol and real meaning. However, as Katz and Fodor (1963) pointed out and our discussion of rationalism will show later in this text, this concept of primitives has its own problems.

Heuristic Artificial Intelligence Now

Searle's allegations that computers would <u>never</u> be able to understand language denied quite clearly that Newell and Simon's original goal of a "thinking" computer would be attainable. After some re-evaluation of their work and a few feeble attempts to defend their projects, heuristic researchers have since settled on a rather simple defense. They reluctantly accept Searle's argument, but claim that he attacked the wrong type of artificial intelligence. He attacked "strong" artificial intelligence while they are working on "weak" artificial intelligence (Moor 1988, Rapaport 1988).

By making this concession, however, the once envisioned spectrum in heuristic branch between weak and strong changed into two separate camps. They argue that the strong camp, which no one really works in, is attempting to build machines that actually think; the weak camp, which they all are working in, is attempting to program computers to appear to simulate human thought.

However, where natural language is concerned, questions of real semantics eventually need to be addressed. Recognizing the problems involved with referents, the modern science of linguistics considers this approach to semantics to be hopelessly flawed (O'Grady et al. 1989). So what we are left with is the recognition that a computer can be programmed to use the symbols of natural language; but at some point, to interact in language, the computer must be able to assign some form of real meaning to words, not a determined set of qualities. In the case of weak researchers, the question is whether computers can be programmed to be so dexterious in language that they can pass Turing's Imitation Game without an understanding of the words they use. These weak heuristic researchers claim that a powerful enough computer could manipulate the symbols of natural language well enough that the simulation of human thought would convince humans that the computer is actually thinking. William Rapaport writes:

> Understanding has to do with meaning, and meaning is the province of semantics. Several recent attacks on the possibility of a computer's understanding natural language have take the line that computers can only do syntax, not semantics, and, hence, cannot understand natural language. Briefly, my thesis in this essay is that syntax suffices (Rapaport 1988).

Rapaport's position, due to the framework of computers, is that held by the heuristic branch. It believes that outward symbolic competence is the guiding force behind the use of natural language, and that formally <u>defined</u> meaning is needed for success in natural language acquisition and usage. Though heuristic researchers will concede that questions of real semantics are important, they argue that at the present time research can first concentrate on developing computers that use the symbols or words of language correctly. Once syntactic ability is confirmed, they believe, research into semantics can then be considered--if necessary.

Conclusion

With their restriction to mere symbol manipulation, can computers gain the ability to acquire and use natural language with the effectiveness required by everyday social interactions? Resolving that issue is the focus of the next two sections. Searle showed through his Chinese Room Argument that computers cannot "think" because they do not have the adequate hardware to understand the semantic content of words. The question now becomes whether the dexterous use of natural language without semantics will allow computers to communicate effectively in spite of their handicap.

In the next section we will discuss the philosophical considerations of heuristic artificial intelligence that are a result of the hardware of computers. By identifying computers through the terminology of the humanities in both philosophy and rhetoric, we can better discuss their capabilities with relation to human capabilities in the real world.

RATIONALISM, DIALECTIC, AND COMPUTERS

Despite their often complex surface capabilities, digital computers are relatively elementary machines working through rapid, but simple, calculations. Though multifaceted higher level programming languages like Pascal, FORTRAN, and LISP can be used to access computers, at machine level computers work by synthesizing all information into simple binarisms of "charged" and "not-charged" states. Even the binary arithmatic features of ones and zeroes commonly connected to these states are made through the interpretation of programmers, not the computers. By putting together strings of these charged or not-charged states through programmed heuristics, computers can represent things in memory, most commonly numbers (Reges 1987).

These points are important because a popular misconception held by and about heuristic artificial intelligence is that better computers through future technology will allow us to develop thought and natural language use in them. In reality, the computers we have now and will have in the future only represent faster and stronger versions of that machine invented by Atanasoff and Berry nearly a half century ago. From the largest supercomputer to the simplist calculator, computers are weaker or stronger versions of the same machine: they are all binary digital computers, Von Neumann machines. The difference between the capabilities of digital computers depends only on their speed, power, and software.

Ironically, computer hardwares gain such applicability and power from their extreme simplicity. Whereas biological beings work through integrational and unpredictable neurological processes, computers work freely without meaning to slow them down. With the human brain, even the simplist of mathematical calculation has some form of meaning involved: dollars, apples and oranges, 1-2-3. For computers, calculation is just charges moving around in formal binary electronic frameworks. The meaning that humans possess is not used by the computer, and the responsibility for corresponding meaning to outputted information from computers rests only with their users.

Some characteristics that define computer frameworks are as follows:

- -Computers are formally systemic.
- -Computers as binary calculators rely on deductive logic.
- -Computers as formal systems require formal heuristics (software).

-Computers cannot associate real meaning to symbols, restricting them to syntactic operations.

Paradoxically, as Searle points out, whereas these characteristics allow computers freedom from meaning in calculation, they also deny computers the abilities to achieve thought (Searle 1984).

In this section, we will take a closer look at computers. Through this discussion of the computer through an identification of it in philosophy and rhetoric, the capabilities and limitations of computers will become clearer later in the text. This road has been travelled before by Dreyfus (1979) and most recently by Winograd and Flores (1986). Though overlapping some of their work, this section will make stronger a couple of their points and provide a slightly different theoretical angle for reference to rhetoric. Our goal is to identify the philosophy beneath the heuristic branch so we can test its theoretical compatibility with theory in natural language.

Rationalism and the Computer

In our time of technology, our society rarely asks <u>why</u> things are the way they are without immediately following with a question about <u>how</u> that knowledge can be applied. Nowhere is this more apparent than in heuristic artificial intelligence. Whereas other fields attempt to touch base with some groundwork in philosophy, heuristic artificial intelligence is content to assume that it is on the right path, rarely trying to determine whether its assumptions are philosophically sound. Although artificial intelligence researchers roll their eyes when those "philosophers" approach their work, we find that their lack of knowledge about philosophy is actually restricting their work.

This restriction occurs because the formally systemic framework of computers forces research on them to rely strictly on the doctrines of rationalism. Preceding computer science by some two thousand years, Plato and Aristotle first outlined the basics of rationalism in which reality was first understood as inherently formally systemic. Underlying almost all current paradigms of thought in western culture, Plato's metaphysics and Aristotle's categories laid the foundation for their concept of a formal universe built on primitives and rules (Kent 1989). Rationalism specifies that reality can be codified into universal concepts and formalizations that directly mirror the processes of the mental and physical universe. It allows empirical science and its philosophy to categorize, label, and formalize reality, giving us the ability to build higher levels of structure by understanding the structures beneath. Reality through rationalism can be viewed as ultimately deterministic in which knowing the primitive elements of reality and how they interact would allow one to determine the future movements of all matter.

As in all formal systems, rationalism's formal system of reality has certain conditions that need to be met. First, formal systems are built on basic elements, individual items to be manipulated. Second, formal systems require strict rules that dictate how the elements interact and influence one another. For example, consider a billiards table and pool balls as a system. The pool balls represent the elements to be manipulated with the table representing the constraints of their surroundings. According to rationalism, the pool balls follow specific physical rules of motion dictated by physical laws that can be formalized directly into mathematics. Any deviance from these rules is viewed as either the fault of the measuring device or a flaw in the system or both. In an "ideal" formal system, all future actions can be determined by those in the past. Formal systems are inflexibly deterministic.

But the rationalist conception of a formal systemic reality specifies a need for "primitive" elements upon which all reality is built--an indivisible "atom," an undeniable elemental "truth." All through the history of rationalism, scientists and philosophers have tried and failed to identify these primitives, but their existence has always been assumed. This blind faith is necessary, because without the existence of primitives, rationalism's foundational belief in a formally systemic reality falls apart (Wittgenstein 1959).

Rationalism in the spirit of Aristotle has taken on many forms and dominated Western philosophy as scientists, philosophers, rhetoricians, mathematicians, and logicians started concentrating their efforts toward formalizing their analyses of reality. In science they searched for the basic primitives of matter and formalized physical interactions. In logic and rhetoric, they searched for undeniable "truths" and developed heuristics of human reasoning in the form of first order predicate calculus (Russell 1959). Later, in linguistics, cognition, and psychology, they searched for elements of "deep structures" of language and mind.

With its assumption of formal systemic reality, the rationalist epistemology supports the conception that eternal forms and categories are the center of all things (Kent 1989). These categories, rationalism asserts, are formal and inherent in the universe, and need only to be discovered by probing beneath the obvious for further truths. Somewhere, it was believed, a structure or structures guide reality in a deterministic way. And to isolate and formalize these structures became the duty of empirical studies in the Kantian tradition. Finding the "primitives" of reality, philosophers could then discover other higher level aspects of reality through deductive heuristics.

Heuristic artificial intelligence is a direct product of rationalism. In their systemic framework, computers deductively manipulate elements (data) through formal heuristics (programs). Computers work on the assumption that every statement or piece of information can be synthesized into bits of "truth" or "not-truth" at a basic level. When Newell and Simon proposed their Physical Symbol Hypothesis, they claimed to be following the doctrines of rationalists like Frege, Russell, and Whitehead (Newell and Simon 1981). They used the theories of rationalism by assuming that the human brain as part of reality is also formally systemic, working with primitives and formal heuristics when it thinks. Therefore, they concluded, the two machines, brain and computer, were accomplishing the same task.

So why is this connection between heuristic artificial intelligence and rationalism important? To answer this question, we turn to Winograd and Flores' work in Understanding Computers and Cognition. In one of the more surprising turnabouts in artificial intelligence, Terry Winograd, one of the most important heuristic branch members of the 1970s and early 1980s, is now one of the branch's strongest critics. In this text regarding the capabilities of computers, he and Flores argue against using computers in artificial intelligence because computer science is too reliant on the doctrines of the rationalistic tradition of Western culture:

> Current thinking about computers and their impact on society has been shaped by a rationalistic tradition that needs to be re-examined and challenged as a source of understanding (Winograd and Flores 1986).

But their assessment needs to be taken even one step further, though, because the rationalist paradigm does more than "shape" heuristic artificial intelligence research. The formally systemic hardware of computers forces research done on them to rely on rationalism. With their need for determined truths and formal logic, computers, with their formal frameworks, are the representation of rationalism in machine form (Dreyfus 1979). Originally invented for mathematical computation, another product of rationalism, they are restricted to the same paradigm. Therefore, heuristic artificial intelligence does more than just follow rationalism; it is dependent on it.

In regard to developing human intelligence on computers, the formalistic, systemic framework of computers forces heuristic research to assume that human reasoning and natural language are also formally systemic. Otherwise, computers would provide incompatible frameworks on which to build human thought and language. Therefore, any questions about the validity of rationalism directly concern any attempts to develop intelligence in a computer.

Computer as Dialectic

With the recognition of computers and heuristic artificial intelligence as inseparably linked with rationalism, we can now map out the position and restrictions of heuristic artificial intelligence with regard to rhetoric. According to Aristotle, discourse separates into two branches, dialectic and rhetoric. Dialectic is a formal system that has two reasoning processes, deduction and induction; rhetoric is informal and has two corresponding reasoning processes, enthymeme and example. Though attempts have been made to subjugate rhetoric to dialectic within the rationalist paradigm, Aristotle in his statement "Rhetoric is a counterpart to Dialectic" (1354a1) saw them as equivalents.

Dialectic, Plato's preferred form of discourse, is based on the assumption that one can arrive at truth by starting from proven truths and working properly through formal logic to a conclusion (Kennedy 1980). Ideally, speakers using dialectic follow syllogisms to deductively develop further truths from true premises. We find this type of reasoning best evidenced in Plato's Gorgias in which the character of Socrates, by virtue of working through "indisputable" truths, comes to logically "correct" conclusions. His opponents, not working from basic truths, are dispatched because of their unsound conclusions.

Rhetoric, best exemplified by Aristotle, is a recognition that truth is not always attainable in social situations, or for that matter even desirable (1355a10). Unlike dialectic in which a person logically arrives at a conclusion, rhetoric requires speakers to start out with a recognition of the desired conclusion. With their desired conclusions as their goals, speakers using rhetoric attempt to persuade their audience that their original conclusion can be accepted as probably true (1355b26). Rhetoric's equivalent to the syllogism is the enthymeme in which one makes probable conclusions based on incomplete sets of premises. Likewise, through examples, as rhetoric's equivalent to induction in dialectic, one can show through past situations that the desired conclusion is probably true (1355a9).

There's an important distinction between dialectic and rhetoric that separates them from one another. Dialectic, as the formal reasoning process, works toward an unknown truth from previously determined primitives of truth through prescribed logical heuristics. Rhetoric, as an informal process in which social considerations play a large role, works toward the speakers' desired versions of truth where truth isn't often clear. Therefore, rhetoric, unlike dialectic, is a social act in which the desires and motivations of an audience need to be considered. So the important distinction between dialectic and rhetoric is that in dialectic reasoning processes, absolute truth is arrived at through proper manipulations of previously determined truths; in rhetorical reasoning processes, one finds the proper means of persuading an audience that the desired conclusion is probably true. Whereas dialectic discovers the conclusion, rhetoric starts with it.

For heuristic artificial intelligence, these distinctions are important as we identify computers in philosophy and rhetoric. Considering the distinctions between the two branches of discourse, dialectic and rhetoric, we can easily identify computers as dialectic, deductive machines. Computers, as prescribed by dialectic reasoning, work with elemental truths through formal deductive logic to arrive at further absolute truth. Their conclusions are the results of their formal activities and, barring malfunctions in the computer hardware, can be considered logically valid and true. Because the programmer is responsible for the correctness of the elements represented in the database and the inputed data, the binary framework operates formally on the assumption that truth exists.

Considering that discourse, according to Aristotle, can be divided into four categories (deduction, induction, enthymeme, and example), we would have to conclude that the binary formal frameworks of computers allow them to reason through only one-fourth of the categories in discourse. Computers through their hardware are restricted to deduction in dialectic analysis--induction requires an ability to reason non-monotonically (Rankin 1988). Their inability to predetermine a conclusion, and their need for formalized truth and complete sets of true premises restricts them from rhetoric altogether. So computers for placement with relation to rhetoric can be defined as strictly dialectic, deductive machines.

Conclusion

Now according to rationalism, these restrictions shouldn't hurt the chances of computers for gaining thought and natural language usage. Dialectics, as long as the primitive truths are programmed into memory, specifies that computers will come out with the correct conclusions. In fact, if rationalism is correct, computers using dialectic could be seen as higher creatures than humans because they operate through ideal truth; while we're forced to consider social aspects and pursue conclusions that might not be true, but desireable.

But attempts to find these primitive truths have proven to be the downfall of both rationalism and the hopes of heuristic artificial intelligence for building a thinking computer. In the next section, we will move beyond the rationalist paradigm by considering reality and natural language as informally systemic parts of an informal reality. In seeing where rationalism's limitations exist, we can also see clearly where the limitations of computers using natural language exist.

PARALOGY AND COMPUTER FRAMEWORKS

The primary concern in heuristic artificial intelligence research since the early 1970s has been natural language. Until the 1970s, heuristic researchers had viewed natural language as a secondary concern to the acquisition of cognitive abilities. They generally assumed that words and sentences take on simple forms that could be labeled and formalized to directly correspond to reality. However, with Winograd's SHRDLU project in the 1970s, the complexity of language became apparent as computers struggled to use even the simplest of linguistic forms (Winograd 1976). Since then, natural language has become the dominant research area in heuristic artificial intelligence as researchers attempt to discover a way for their computers to use natural language effectively. And yet, before we ask "how" computers can be programmed to use natural language, we must first ask "whether" the rationalistic formal frameworks of computers are compatible with natural language.

Considerations of rationalism were the basis on which Newell and Simon originally believed that computers could acquire and use thought. According to rationalism, as set forth by Plato's conception of dialectics, natural language can be used to say things about the world that are inherently "true" or "false." Under this view of natural language, "content" words, such as nouns, verbs, adjectives, and adverbs, directly signify objects and concepts in the physical world (Winograd and Flores 1986). Observing similarities between computer frameworks and the rationalist conception of thought and natural language, Newell and Simon developed their Physical Symbol System hypothesis, citing Frege and Russell's attempts to formalize language into first order predicate calculus as their inspiration. They had correctly recognized that computers met the criteria of thought in rationalism in that these binary machines operate through a process of assigning truth or falseness to a statement and manipulating symbols (Newell 1980).

Conspicuously missing in heuristic artificial intelligence's few discussions of philosophy, however, is a recognition that modern philosophy has identified the limitations of the rationalist paradigm. Many disciplines in the sciences and philosophy, once dominated by a strict reliance on rationalism and its conception of a deterministic reality, now have found evidence that reality is _not_ formally systemic.

So how does this anti-metaphysical philosophy allow us to approach studies of natural language? And further, where does heuristic artificial intelligence fit into a non-rationalist conception of reality and natural language? In this section, we will discuss the the evidence for an informal reality in the sciences and philosophy, then we will discuss the "post-structural" aspects of natural language and their effects on heuristic artificial intelligence. By viewing natural language as paralogical, we will discuss whether computers provide proper frameworks for the acquisition and usage of language.

Paralogy as Opposed to System in Science and Logic

To put it lightly, rationalism has dominated the thought and scientific theory of Western culture. As Winograd and Flores (1986) point out, rationalism has become synonymous with intelligence--

> --as the paradigm of what it means to think and be intelligent. In studies of thought, emphasis is placed on the form of rules and on the nature of the processes by which they are logically applied. Areas of mathematics, such as symbolic logic and automata theory, are taken as the basis for formalizing what goes on when a person perceives, thinks, and acts. For someone trained in science and technology, it may seem self-evident that this is the right (or even the only) approach to serious thinking. Indeed, this is why many

> workers in artificial intelligence find critiques like that of Dreyfus obviously wrong, since they challenge this deep-seated pre-understanding.

Post-structuralist philosophers such as Derrida would even contend that this rationalist mind set is so deeply seeded in Western culture that breaking out of it is almost an impossible task (Derrida 1976). Kuhn, regarding scientific philosophy, argues that the rationalist paradigm restricts scientific growth because it encourages the sciences to be continually forcing observed phenomena into theories dominated by formal systemic rules (Kuhn 1970).

Despite the long tradition of rationalism, however, science and philosophy in this century has found reason to doubt whether reality is indeed formally systemic. These doubts arise because the primitive elements that are essential to rationalism cannot be found. Instead, attempts to determine a formal structure in reality have led many philosophers and scientists to conclude that reality is actually paralogical, not formal systemic. By paralogical, I mean that the primitive elements or truths needed by rationalist philosophy to complete a formalization of reality don't exist; instead, we find that reality is based on uncertainty that defies exact deterministic formalism (Kent 1989).

Empiricism, in the Kantian tradition of rationalism, is based on the assumption that when we work through the scientific methods in analyzing reality, we are actually discovering the mathematical formalizations _inherent_ in the universe. Recognizing that reality tends to operate through patterns, rationalism in science assumes that underneath each structure lies another structure until we arrived at the most basic structure. This primitive structure, upon which all reality is supposed to have been built, is assumed to be formal and codifiable into direct mathematical formulations. So in this light, science, especially since Kant, is understood by rationalists as the attempt to closer formalize reality until an exact formalization is discovered.

However, attempts by both scientists and philosophers to isolate this basic structure have met with repeated failure. At the points at which scientists and philosophers expect basic structure, instead they find only uncertainty, paradox, and slipperyness. When the formal nature of rationalistic epistemology is deconstructed, we find that our universe is based on probabilistic uncertainty rather than primitive structures. To clarify this concept of paralogy, I have chosen two examples from other disciplines, physics and logic.

Paralogy in physics

As Richard Rorty points out, philosophy is split between philosophers that "have remained faithful to the Enlightenment and have continued to identify themselves with the cause of science" and philosophers that consider science to be "no more than the handmaiden of technology" (Rorty 1989). The first approach insists that science discovers truths by directly analyzing our surroundings. These truths are believed to actually exist in physical reality; and through their discovery, empiricists believe that reality can be systematized and formalized. The second philosophical approach sees natural science as a manufacturer of truths. Truth does not exist without the human mind because it is the human mind that determines what is true or not. At best, they believe, scientists can make generalizations about our surroundings, but these generalizations can never be held as absolutely true.

Though most modern scientists, under the guiding hand of empiricism, work through the paradigm supported by the first approach to philosophy, we find that the theories of modern physics encourage us to adopt the second approach to philosophy. Indeed, we have found that a formally systemic nature of physical reality does not exist at all. Instead, quantum physics has found that reality is paralogical.

Paralogy in physics is best evidenced by quantum mechanic's reliance on Heisenberg's "uncertainty principle" in the treatment of matter's wave/particle duality. In quantum theory, matter from the smallest particle to the largest mass can be treated as both a wave <u>or</u> a particle in the same instances. Unlike classic Newtonian physics and Aristotle's metaphysics in which an inherent determinism in physical reality was an essential feature, the uncertainty principle specifies a sense of randomness in matter. Richard Feynman, a major American physicist, states the Heisenberg uncertainty principle as follows:

> If you make the measurement on any object, and you can determine the x-component of its momentum with an uncertainty dp, you cannot, at the same time, know its x-position more accurately than dx=h/dp, where h is a definite fixed number given by nature. It is called "Planck's constant" . . . The uncertainties in position and momentum of a particle at any instant must have their product greater than Planck's constant (Feynman, Leighton, and Sands 1965).

Put simply, the constant h always forces a paralogical gap between wave and particle, creating a sense of "slipperiness" between momentum and position. The uncertainty principle ensures a paralogical gap between the treatment of matter as a wave (momentum) and the treatment of matter as a particle (position).

Based on its need for a deterministic reality, rationalism would assume that at some point particle would become wave to create a "wavicle" in which both momentum and position could be measured simultaneously. However, quantum theory specifies a need for the two to be always separate (Tarozzi and van der Merwe 1988). The closer one determines position, the farther one is from specifying momentum; the closer one determines momentum, the farther one is from determining position.

This uncertainty in physical reality is an example of the paralogical nature of physical reality. Our mathematical treatments of physics must be viewed as generalizations rather than strict formalizations of reality. Scientists even leave Schroedinger's equation, the essential formula of quantum theory to determine the energy states of particles, open to further additions, recognizing it as only an approximation to be continually improved by observation.

Therefore, reality does not conform to formal mathematics and formulas; rather our mathematics and formulas only approximate the actions of reality. This uncertainty in physics shows us that formalization (and thus rationalism) fails to do anything more than generalize about the actions of physical reality. We find that physical reality is indeterminate; therefore it denies formal systemization.

Paralogy in logic

Logicians encountered paralogy as they strove to determine the elements of human reasoning. Aristotleian dialectics, the foundational basis for logic, specifies that logic contains two branches of reasoning, deduction and induction. Deduction, represented by the syllogism, rests on the assumption that two "known truths" can be used to derive a sound conclusion. Induction bases the proof of a proposition on an ideally infinite number of similar cases (Bergmann 1980). Aristotle and his rationalist heirs viewed induction as a form of logic to be used in cases where truths were not readily available for syllogistic reasoning.

In dialectics, syllogistic reasoning requires an eventual identification of indisputable knowns to complete sound logical formalization of reality. In

Aristotle's dialectics, these primitive elements needed to exist in his conception of a codifiable universe.

However, rationalists' attempts to identify these knowns have continually failed throughout history. Bertrand Russell states:

> It appeared that, from premisses which all logicians of no matter what school had accepted ever since the time of Aristotle, contradictions could be deduced, showing that something was amiss but giving no indication as to how matters were to be put right (Russell 1959).

Gottlieb Frege, Bertrand Russell, and Ludwig Wittgenstein worked diligently to resolve these "contradictions" that undermined rationalist logic's conception of a formally systemic reality. Russell in correspondence with Frege said that "Frege was so disturbed by this contradiction that he gave up the attempt to deduce arithmetic from logic, to which, until then his life had mainly been devoted" (Russell 1959). Russell, who claimed that one of his three goals in life was to "persuade myself that something could be known," repeatedly met with paradox where he felt knowns should be found (Russell 1959). Wittgenstein, after spending years searching for primitive elements, abandoned rationalism and instead turned to attack it. In 1953, he published his <u>Philisophical Investigations</u>, an outright attack on his own Tractatus Logico-Philosophicus. In Philisophical Investigations he argued that reasoning and language can't be context-free from human interpretation as a rationalistic conception of formal systemic reality would contend; they require some form of pragmatic organization in which our experience in coping with everday problems is incorporated. Wittgenstein states:

> Both Russell's 'individuals' and my 'objects' were such primary elements. But what are the simple constituent parts of which reality is composed?--The bits of wood of which it is made? Or the molecules, or the atoms? Simple means: not composite. And here the point is: in what sense 'composite'? It makes no sense at all to speak absolutely of the 'simple parts of a chair' (Wittgenstein 1953).

He later states that:

> To the philosophical question: "Is the visual image of this tree composite, and what are its component parts?" the correct answer is: "That depends on what you understand by 'composite'." (And that of course is not an answer but a rejection of the question.) (Wittgenstein 1953).

Rationalism in logic found itself in the same situation as physics. Reality could not be formally systemetized because primitive truths or knowns could not be identified. In the case of physics, uncertainty, not formal system, was found at the basis of physical reality; meanwhile, in logic, paradox, not formal system, was found at the basis of human reasoning.

These two field's discoveries are similar in that they example the paralogical nature of reality. Reality is not formally systemic at its roots; rather, it is indeterminate and paralogical. Our formalizations of reality, therefore, are based on assumptions, allowing us to accept them as nothing more than approximations and generalizations of our surroundings.

Society and Language

Considering that scientists and philosophers have shown other parts of reality to be paralogical, can we accept rationalism's assumption that natural language is formally systemic? Though our prescriptive grammar books attempt to lay down specific rules about the "right" and "wrong" of natural language usage, language is hardly a static feature in human society. Rather, it is a fluid medium that continually changes over time. Despite these constant changes, however, natural languages tend to settle down into common syntactic patterns that sentences generally follow. In English, the general pattern is subject, verb, object (SVO). Linguists in the last century, following the cues of empiricism, have often looked at these patterns as an indication of some form of "deep structure" that underlies all language forms.

Despite the empirically based assertions of the formal nature of natural language, though, do we really have any reason to believe that language must be formally systemic? Or is this a case, as Heidegger and Derrida assert, where the rationalist paradigm and its insistence on formal system is restricting us from understanding natural language in other more pragmatic ways? (Derrida 1976, Heidegger 1962)

First we'll consider the position of rationalism. Rationalism insists that language must be viewed as a formally systemic process that is universal in reality. Plato originally argued that the primitives of language are inherent in humans because they are brought from a past life. Aristotle tried to codify these formally systemic features in his Dialectics, but then wrote his Rhetoric as a recognition that this formal system was not in actual use in social interactions (Kennedy 1980). He, and rationalists since, have viewed the deviances from the "ideal" system of language as pragmatic taintings of the formal rules that supposedly exist in reality. The rationalist views language as a strict systemic process in which the universal rules can be formalized into logical structures.

This view of a formal systemic language, though, has not been supported by philosophical inquiry into natural language in the twentieth century. When rationalists, Frege and Russell, tried to identify formal language in terms of dialectical analysis, their attempts to develop language in the form of first order predicate calculus failed. Their research actually drew a very different conclusion than their atomist upbringing had taught them to expect. Attempting to isolate the primitive elements or "truths" that were necessary for a formal systemic language, their efforts only found paradox where they thought primitive elements would be discovered (Russell 1959). Language, as they found, could not be formalized because the elements necessary for such a formal system could not be isolated. Wittgenstein, whose own attempts to isolate the primitive elements of language also failed, took these failures as an indication that the primitive elements of reality do not exist (Wittgenstein 1953).

Natural language as Wittgenstein concluded and Rorty later confirmed is paralogical much like physics and logic (Rorty 1989). The observance of pattern qualities of languages does not necessarily indicate that a formal system is underneath the language guiding it and unifying it.

Now just because no formal system underlies language does not imply that language has no structure, or, for that matter, that it is not a system. On the contrary, natural language follows definite patterns and conventions of the social groups that generate and use it (Halliday and Hasan 1989). The problem with the rationalist conception of formal system in natural language is that it ascribes to those conventions a strictly ruled quality in which language supposedly conforms to mathematical formulations. Formalized natural language supports the false notion that language is static, context-free, and not socially dependent.

Rather than a formal system, natural language is an informal system with a structure that is as indeterminate as the societies that generate and use it (Halliday and Hasan 1989). Like physics with its generalizations of physical reality into formulas, linguistic formal analyses of natural language are only generalizations, not direct taps into truth. So we need to approach them as such. We need to always remember that natural language conventions in a society can be looked at separate from that society, but we cannot deceive ourselves into believing that natural language can be extracted and formalized without ties to its social environments. In other words, as a socio-semiotician like Halliday would point out:

> . . . we cannot operate with the concept of a sign as an entity. We have to think rather of systems of meaning, systems that may be considered as operating through some external form of output that we call a sign, but that are in themselves not sets of individual things, but rather networks of relationships. It is in that sense that I would use the term 'semiotic' to define the perspective in which we want to look at language: language as one among a number of systems of meaning that, taken all together, constitute human culture.
>
> For some linguists (e.g., Chomsky 1957; Lamb 1966) the preferred mode of interpretation is the psychological one, in which language is to be explained in terms of the processes of the human mind or the human brain . . . For us, then, the perspective primarily adopted--not to the exclusion of the others, but because this is where we look first to seek our explanations for linguistic phenomena--is a social one. We attempt to relate language primarily to one particular aspect of human experience, namely that of social structure (Halliday and Hasan 1989).

One can look at language conventions without their society and even attempt to formalize them as Chomsky has done in Transformational Grammar; but one must also recognize that those formalizations as in physics are only generalizations because the lack of primitive elements forces natural language to be paralogical. One must also recognize that all languages are essentially dependent on their social environments and cannot be extracted totally from them.

Paralogy in Meaning and Computers

At this point, we will turn to the more practical matters of language in artificial intelligence to show where the paralogical nature of language will cause insurmountable barriers to heuristic artificial intelligence. Despite the assertion that computers provide an improper framework for natural language, most people have encountered computers that can "speak" audibly or use written words as prompts on a moniter. For instance, the cash register at the local supermarket might read and sound out prices; a car signals in words that one of the doors is ajar; or an electronic game for the television guides the player verbally. Most software programs these days provide specific prompts that tell the users what information is needed for the next step. Indeed, many computers on the market have the ability to signal a human through verbal or written words. In comparison with what humans accomplish with language, though, we wouldn't consider these computers "intelligent;" but they are using words.

When we speak of using language, more is expected than the ability to manipulate words. Language is a socially interactive medium in which thought is expressed through symbols. The ability to manipulate these symbols, though, is not sufficient evidence to claim any sense of "intelligence." Of course, the point being driven at is that the ability to use language requires an ability to accomplish more than the symbolic manipulations of speech and written text; an ability to correspond real semantic meaning to symbols is also essential.

As discussed in the previous chapters, however, computers are purely symbolic machines with no conception of the real meaning of words. While human beings can experience the meaning behind a word and gain a semantic understanding, computers must rely on their programmers to formalize definitions and contexts in which each word is used. According to rationalism, this approach to language would require a great expended effort, but it would be possible. But if we are to accept language as paralogical, such formalizations are impossible.

First, let us consider definitions of words. Newell and Simon originally hypothesized that the brain operates by manipulating physical symbols. These symbols, following the rationalist conception of reality, reflected directly real objects in reality. Rationalism asserts that a direct connection between symbol and meaning, syntax and semantics exists. This issue was put down directly by Montague's homomorphism between syntax and semantics:

1. For each syntactic category there is a corresponding semantic object.
2. For each syntactic operation there is a corresponding semantic operation. (Hausser 1989)

So if a computer could properly manipulate the syntax of a language, it would also be manipulating the semantics of those symbols also, since symbol and meaning were directly connected. If we look through the eyes of rationalism, at some point, syntax and semantics should connect to form a point of syntax/semantics.

In post-structuralism, however, the connection between word and symbol is much looser and slippery, making definitions impossible to formalize into primitives or referents. For example, let us consider the problem with formalizing a set of referents for the word "car." We start by looking in the dictionary and thesaurus for definitions:

Dictionary:

Car:
1. An automobile.
2. Any of various wheeled vehicles.
3. The enclosed platform of an elevator.

Thesaurus:

Car: 1. auto
2. motor (car)
3. automotive vehicle

Obviously, each of these definitions rely on other symbols that need to be defined with referents themselves. So we look up the meanings of the other words and find more undefined words. Eventually we have a huge collection of descriptions of cars, types of cars, purposes for cars, etc. But still, we find that our abstractions are built on other abstractions, without any solid conception of what the symbol "car" really represents. Just the number referents needed to clearly define the one basic symbol "car" grows quickly to a staggering amount.

Realizing that the dictionary is leading us more into abstraction than specificity, we all sit down with a piece of paper and start defining what the symbol "car" means to each of us. Soon it becomes apparent that though we càn all generally agree on what a car is, we all have different, often opposite meanings for the word. One person who has experienced a great amount of engine trouble has a negative tinge to his meaning of "car;" while another person who always saw her car as a symbol of freedom has a completely different meaning for the word. Soon, other associations start to take their place in the meaning of the symbol "car:" car sickness, family vacations, driving to college, etc. Once again we have found that the specificity needed to formalize meaning into referents for a word only leads us into abstraction.

Of course, the problem I'm driving at is that semantics cannot be effectively formalized into referents and primitives as heuristic researchers believe. Most heuristic research today attempts to assign referents of meaning to symbols to give computers some sort of semantic ability. Schank argues for primitives of natural language upon which all meaning is built (Schank 1975). And yet, as Russell, Frege, and Wittgenstein already found, those primitives do not exist. From the car example, we see that meaning for a symbol is reliant on many idiosyncratic and social contextual associations that are beyond the capabilities of a computer to acquire. So what the heuristic branch is left with is a relatively simplistic synthetic conception of meaning when compared to a human's sense of meaning. Whereas a car might be a [+ vehicle], [+ four wheels], [- animal], [+ animate], etc. (as far as the programmer wishes to go) to the computer, it is infinitely much more to a human being.

We have found that like other aspects of reality, language too is paralogical. As in the wave/particle aspect of quantum physics, a paralogical gap separates symbol from meaning. Derrida developed the concept of this separation in his works on differance (Derrida 1976). Language, he explained, associates semantic meaning with symbol; but when one attempts to isolate the meaning of a symbol, it becomes slippery and playful. Like the wave and particle, meaning and symbol are inseparably joined, but never directly connected as in rationalism.

So natural language cannot be separated from a society and an individual's idiosyncratic experiences (Halliday and Hasan 1989). The forms that are agreed on by the sciences of language shouldn't be mistaken for universal truths or formal system that underlies natural language. Rather, we need to see natural language formalizations as only generalizations.

Synthetic Language

The crux of the problem for computers with natural language is that they are not compatible systems. Computers are formal systems. They need information synthesized into primitive elements and formal heuristics. Mathematics works fine with computers because it has been developed as an ideal formal system in which elements and formulas are available. Mathematics doesn't generalize about the real-world; rather, it builds itself from its own paradigm. Natural language, however, is part of a paralogical reality and does not rely on formal system. Therefore computers with their restrictive rationalist frameworks will never be able to use natural language as humans do.

The anticipated argument to the conclusion that natural language is not a formal system and therefore incompatible with a computer's framework is that linguistics can generalize so well that a quasi-natural language can be developed that fits the computer framework. These arguments come from those self-proclaimed "weak" heuristic researchers who feel that a formal system's representation of natural language is sufficient for language use.

Their argument, derived from a rationalistic view of language, is that questions of real meaning are far less relevant if the computer can outwardly simulate intelligence (Smith 1988, Rapaport 1988). They would argue for the use of a synthetic representation of language that is formally systemic and purely symbolic.

Really, the reason heuristic researchers like Rapaport advance such synthetic forms of natural language is because these restrictions on reality are what it would take to graft a sense of natural language onto a computer framework. Heuristic artificial intelligence's only chance of success is for it to shut its eyes from research in language and to attempt to restrict language to fit their computers.

Besides the obvious difficulty of fabricating a language in denial of how natural language actually works, some rather basic problems immediately confront this approach to artificial intelligence. For one thing, the computer, as Searle pointed out, cannot think because it has no real semantic abilities. Second, the computer cannot use language syntactically correctly because natural language, as I've pointed out above, cannot be totally formalized and no "correct" exists.

We've seen the results of attempts to synthesize language: programmers trying to develop endless parsing schemes to anticipate the many sentence structures that humans use; computer databases choked with referents for even the most restricted semantic abilities; computer programs with a few behavior scripts struggling to accomplish tasks that humans don't even think twice about. Heuristic artificial intelligence through much expended effort, time, and money has developed simplistic programs that cannot come close to communicating effectively with humans.

A rule of carpentry is that one should always use the correct tool for a task because using the convenient wrong tool usually ends up causing more work with bad results. We have such a situation with heuristic artificial intelligence. Computers are the wrong tool for thought and natural language; yet, heuristic researchers have stubbornly insisted on forcing thought and natural language into computer frameworks with bad results.

Conclusion

In this section we discussed the paralogical aspects of natural language and showed how they provide an insurmountable barrier to heuristic artificial intelligence. Language, like other aspects of reality, is anti-metaphysical in that it has no formal system underneath that can be codified. Therefore, since computers <u>need</u> a formal system language to be programmed into their memory, we have two choices. Either we can satisfy ourselves with pursuing synthetic formalizations of language that won't ever provide effective communication in social environments; or we can recognize the computer as an incompatible framework for artificial intelligence and set it aside.

The next section will discuss a different approach to natural language through rhetoric. Rhetoric, as a pragmatic use of natural language, can provide guidance as to what type of machine could use natural language effectively without forcing research to settle on a synthetic formalization of language that conveniently fits computer frameworks.

PRAGMATICS AND RHETORIC

To this point, our discussion has primarily centered on the theory, philosophical position, and capabilities of computers to acquire and use natural language. As the technological product of applied theories of rationalism, computers are shackled by the same difficulties and restrictions that face all research done through the rationalist paradigm. As in physics, logic, and linguistics, formal analyses in artificial intelligence only allow a simplistic, restrictive concept of natural language that is inadequate for pragmatic use in social environments.

Does this mean that computers cannot use language? Yes and no. Obviously, one cannot deny that the programs such as ELIZA, SHRDLU, and CYRUS have shown an ability to recognize input and respond to inputted information with relevant answers. Schank's work with language has provided some practical applications in the growing field of expert system software. Winograd, though soundly proving that computers cannot be artificially intelligent, encourages research to look for the many potential applications of computers using natural language in helping humans accomplish tasks better. Obviously computers that can parse sentences and correspond in a user's language would be valuable due to their accessibility.

An important point to remember, however, is that the formal hardware of computers will always serve as a restriction to their ability to successfully use natural language as humans can. As programmers try to further formalize natural language and human behavior into heuristics, a point will always exist at which the limits of their computers, their patience, or their lifespans will force them to recognize that a universally adept computer in natural language isn't feasible. And for what will all their time, genius, and money have gone for? A computer that can carry on a simplistic conversation in English? Even if we did have powerful enough hardware, the complexity of natural language would force most of the computers' efforts to be spent on communication, not the problem-solving applications for which they could be most useful.

Continually awed by the powers of the human brain, I can't help but think that perhaps a better approach could be taken toward artificial intelligence. Indeed, the mindset that computers are the answer to artificial intelligence has turned into a restrictive paradigm that seems to be holding back research in the discipline from looking for better machines on which to build artificial intelligence. Researchers like Winograd who have allowed themselves to step out of the paradigm have often found that a view from the outside shows clearly how strictly confining computers can be to research in artificial intelligence. The problem with the discipline of artificial intelligence is that researchers are asking how natural language fits their computers rather than asking the more relevant question of what type of machine is needed to acquire and use natural language. Therefore, the restrictive hardware of computers is forcing researchers to approach the problem from the wrong direction.

So at this point in the text, we will set computers aside. Surely, there remain many amazing applications for them in the future, but artificial intelligence as a pursuit of a thinking machine is not one of them. With the rest of this text, we will approach the discipline from a new angle. Instead of prematurely settling on a machine, we will look at what the features of natural language tell us about the types machines that would be able to use language. Of course, our focus turns from computer science to the humanities as we need to find out what humans do with natural language. In this way, we can determine also what our machines need to do with natural language.

In this section, we will discuss the pragmatic aspects of natural language through considerations of the purposes and uses of rhetorical discourse. Though certainly not the only angle we can take toward this search for a proper machine hardware for artificial intelligence, rhetoric provides an excellent example of discourse processes in use in social contexts. By allowing established fields such as rhetoric to mentor research in artificial intelligence, our research can go beyond the mindset that forces research to focus on parsing sentences and writing relatively simple heuristics of human behavior. Instead, we can understand directly what we want our machines to accomplish with natural language in social contexts.

Rhetorical Ability as a Needed Quality

Rhetoric as defined by Aristotle is "the faculty of observing in any given case the available means of persuasion." Referring back to Turing's Imitation Game, we can see rather simply that rhetoric is a skill that any artificially intelligent machine would need to have to pass the test. The machine needs to <u>persuade</u>

humans that it too is a human being. So for successful operation as an intelligent entity, the machine needs to have the ability to find the proper means of persuasion to successfully convince a small social group that it is human.

At first, this might sound like a solution to an isolated case, but rhetorical discourse is a prevelant part of almost all uses of natural language. Whether we are writing out a grocery list, discussing a movie with a friend, or speaking in public, we are to some degree attempting to persuade members in our social environment to act or believe something that we wish them to consider "correct." When communicating through natural language, humans are in essence always rhetorically persuading others in their social groups to accept a particularly ideisyncratic view of reality (Rorty 1989).

Certainly, many artificial intelligence researchers who are used to approaching natural language textually through grammar features of sentences will find this approach from rhetoric to be reaching too far too quickly. No doubt, they will point out that this approach is too sophisticated when we haven't even established the "basics" of natural language use. But what are the "basics" of natural language? Afterall, children learn to use rhetoric long before they learn how to put words and phrases together. A human baby's first acts involve rhetoric: they cry when they're hungry, they smile because it nets them attention, they fidget when they feel neglected. Essentially, humans learn at a very young age to persuade the members in their social environments (mom and dad) to do what they want. Rhetoric isn't necessarily among the sophisticated aspects of language; rather, it is among the first things we learn as human beings.

Language as a Social Act

Instead of formalizing the conventions of language, rhetoric allows research in artificial intelligence to approach natural language more properly as a social construction. Due to its paralogical nature, natural language represents a social generalization rather than a direct reflection of a truth that is "out there." Informally systemic like the social groups that use it, natural language expresses and promotes the user society's interpretations of reality (Rorty 1989). Therefore, a contextual understanding of natural language within the social group that uses it is essential to proper acquisition and usage (Halliday and Hasan 1989).

Actually, social groups can consitute any grouping of people that communicates ideas among its members with a form of natural language. On a larger level, "English speaking people" represents a social group because it shares commonality through a class of natural language. On a smaller level, "doctors in Iowa" represents a social group because it shares commonality in language that requires contextual understanding in medicinal practices in Iowa. Humans operate effectively in those social groups in which the conventions of language that allow a member to communicate are understood. Therefore, natural language users must understand the contexts as well as the textual conventions of the societies in which they wish to operate (Halliday and Hasan 1989).

This need for social context in addition to textual abilities in successful natural language acquisition and usage provides an important distinction between informal, pragmatic theories of natural language and the formalistic theories of rationalism. In rationalism, natural language and truth can be essentially separated from their social context due to their supposed formally systemic nature. Language and truth as mirrors of the formal reality are therefore thought by rationalists to contain a codifiable truth that can be "found" through empirical inquiry outside of social context. This believed direct attachment to reality through language and truth accounts for the rationalists' assumption that primitives of reality exist to be discovered.

Generally viewing language as a socially generated medium used to understand reality, pragmatic, social theories of language locate truth within the accepted beliefs of social groups. Therefore, truth is "made" by social groups rather than "found" in reality (Rorty 1989). At first, this conception of truth as a social construction often makes persons brought up under the rationalist paradigm uneasy because it advocates that the "discoveries" made by science are only more useful manufactured generalizations of reality (Kuhn 1970). Due to the paralogical nature of reality in which formalizations of reality are impossible, though, theories must be recognized only as useful generalizations of our physical and social environments.

Identified within the context of a social environment, truth becomes informal and without absolutes, not conforming to any universal guidelines.

Lamenting that, despite the success of rationalism, as a theory it had been unable to determine an indisputable "truth" in reality, Kant called it "a scandal of philosophy and of human reason in general" that Western philosophy had not been able to answer the question "How can I know whether anything outside of my subjective consciousness exists?" Heidegger points out that "the 'scandal of philosophy' is not that this proof has yet to be given, but that such proofs are expected and attempted again and again" (Heidegger 1962).

With this conception of language as an informal system generated and used by social groups, natural language must be viewed as inseparably intertwined with the social groups that use it. Natural language is acquired through interaction with social groups and is used within social contexts. Rorty claims that "truth is a property of linguistic entities, of sentences." Therefore, the ability to correspond in natural language with social groups and their interpretations of reality is an essential feature of an intelligent entity.

With the placement of truth within the beliefs of social groups, the importance of rhetoric to the use of natural language becomes clearer. As a medium of persuasion of socially generated versions of truth, rhetorical discourse represents the way in which language-using members of a social group help generate and promote their social group's conception of truth. Therefore, a machine's ability to acquire natural language hinges on its ability to learn from and correspond pragmatically with the social groups in which it is meant to operate.

As a side note, I find it ironic in a rationalistic field like heuristic artificial intelligence, where truth supposedly can be codified into primitives, that the test of intelligence is to have the computer persuade humans that a falsehood is true--the computer is human. If one accepts that such primitives of truth exist, one can't accept that lies are available to the computer since all its concepts are dialectically built on truth.

Pragmatism in Artificial Intelligence

Rhetoric, by understanding natural language acquisition and usage as socially dependent, allows us to approach natural language pragmatically instead of empirically. Therefore, our approaches to artificial intelligence change to reflect a more functional purpose for natural language. Instead of searching for or synthesizing underlying structure, we can instead focus on how language is acquired by the members of societies that generate it. Humans don't acquire natural language usage through an initial understanding of the features of language. Rather, humans learn natural language by recognizing patterns in discourse, allowing the guiding hand of social context to help infants to self-organize the principles of natural language within their own minds.

Actually, Rosenblatt, the first major figure in connectionist artificial intelligence, was the first to advocate this approach to developing human reasoning in a machine. Though he didn't argue against rationalism in artificial intelligence as I have done, he did recognize that formalizing human reasoning processes would be extremely complicated. Instead, he advocated an approach in which machines would be built to recognize and associate patterns in their experiences (Rosenblatt 1962). Approaching questions of intelligence with the human mind as a model, he felt that machines could be built that would be able to organize their own experiences into patterns. This practice would eliminate the need, as in heuristic artificial intelligence, for researchers to formalize or synthesize human reasoning outside of the machine. Self-organizing machines would form their own generalizations about their experiences and associate these experiences with one another through recognition of similarities. Researchers in this approach wouldn't even need to understand why or how the machine organized its experiences, eliminating the complications involved with formalized programming.

Rosenblatt's research showed us that pattern recognizing machines are possibilities. They don't need researchers to program them to recognize specific patterns, only how to associate patterns within different stimulus. In other words, the pattern recognition approach would treat learning by the machine much as we treat learning in humans in that it would allow machines to organize their own patterns of "thought" from the material that they are "taught."

If we extend Rosenblatt's concept of self-organization to language acquisition, we can see that pattern recognition is the best way to develop language capabilities in artificially intelligent machines. Natural language as we've discussed is a socially generated medium that members learn through social interaction. Humans didn't acquire language by having someone or something sit them down and point out that "this is classified as a noun and it goes here in a sentence." Rather, in correspondence with their immediate social groups, they learn to distinguish patterns in social discourse and associate those with other language patterns they had experienced before.

Once enough of these patterns are accumulated, children attempt to join the discourse of their immediate community. Of course, with a limited exposure to patterns and the small society with which they have contact (parents, family members) they start out with something like "mama" or "dada," but this was relevant communication in those social groups all the same. All through life, when humans fail to communicate according to the expectations of their social groups, the social group affected corrects them with proper patterns. In all societies, including academic ones, this correction is an important aspect of gaining and organizing knowledge. When a member advocates a new conception of truth, societies will either correct that member to fit the accepted conception of truth or they will accept that conception of truth and change their own. Likewise, when a machine makes a socially incorrect association between meanings, the society can correct it with the proper course of action.

This concept of the self-organization of language through social interaction presents a superior alternative to formalization of human language processes for artificial intelligence. First, it recognizes that language cannot be formalized due to its paralogical nature, eliminating the need for a tedious synthesis of language by programmers. The machine acts like a human in that it self-organizes its language by distinguishing similar patterns and constantly improving its language competence. Second, it allows the machine to learn the conventions, patterns, and discourse in its social environments, allowing the machine to communicate through the concepts of truth that its social groups have manufactured.

Conclusion

In this section, the argument was made that a pragmatic understanding of natural language can help guide research in artificial intelligence. By asking what type of machine is compatible with natural language rather than asking how natural language can be made compatible with computers, we are able to approach the discipline of artificial intelligence from a new angle. Rhetoric as a pragmatic understanding of language can provide that approach.

Since at one point or another theory needs to touch base with application in artificial intelligence, the next section will provide some practical guidance from rhetoric for the type of machine that can achieve artificial intelligence. Some artificial intelligence researchers familiar with the current dilemmas and roadblocks facing artificial intelligence will probably find it interesting that rhetoric has researched and often overcome some very similar problems. For researchers in the humanities, the next section might provide a bridge through which they can find ways in which their work can likewise offer guidance to research in artificial intelligence.

RHETORICAL NEEDS OF ARTIFICIAL INTELLIGENCE

In the last section, the argument was made that when we want our artificially intelligent machines to communicate with natural language, we want them to use language rhetorically. In comparison to the relatively young field of artificial intelligence, rhetoric is a matured discipline with a long history of established analysis and practical achievements. Though we often seem to assume that our age represents the highest achievement in academic pursuits, in studies of language we increasingly find ourselves returning to theories developed in ancient Greece and Rome to understand how natural language operates in social environments.

Presently in the philosophy of language, the discipline of rhetoric is undergoing a change similar to that in artificial intelligence. Through the ideas of Wittgenstein, Heidegger, Rorty, Derrida, Grice, Searle, among many others, the philosophy of language has challenged the rationalist paradigm of formalism that has dominated and often restricted the directions of research in natural language. Commonly labled "post-structuralism" to separate them from the rationalist paradigm that came before them, these theories advocate an anti-metaphysical, decentered, and paralogical understanding of reality and natural language. They approach language as a pragmatic activity that cannot be codified into formalisms (Rorty 1989).

Like most studies in western culture, rhetoric too has been dominated by rationalism's insistence of formal system. We can trace the basis of formally systemic rhetoric to Plato and Aristotle's arguments against the pragmatic rhetorics of the sophists (Kent 1989). The sophists, best represented by Antiphon, Gorgias, Isocrates, and Protagoras, treated discourse as a social instrument for use in the daily activities of Greek legal, social, and political life.

> For Plato, this kind of pragmatic approach to discourse obviously posed a direct threat to his entire metaphysics, and for Aristotle, Sophistic materialism lead directly to an untenable relativism that threatened the foundation of his categories . . . . For epistemological foundationalism and a metaphysics of presence to endure, Sophistic philosophy, which consisted of rhetoric in its practical uses, had to be eradicated, and for the most part it was (Kent 1989).

Despite our inability to regain the sophistic position with regards to language, we find that post-structuralism in both linguitics and the philosophy of language is advocating a return to understanding natural language as a pragmatic, contextual medium.

However, looking at the works that form the framework of classical rhetoric such as those of Isocrates, Aristotle, Cicero, and Quintillian, we might even say that rhetoric has never completely fallen into the rationalist paradigm. For example, despite the insistence on formal system in all of his publicly circulated works, Aristotle's Rhetoric, from which most of our analogies to artificial intelligence will be made, has a touch of sophistic influence in it due to his recognition that social interactions generally defy formalization (Kennedy 1980). Therefore, though it could be identified in the rationalist paradigm due to its author, the Rhetoric can also be useful due to its excellent analysis of the informal nature of natural language usage. Aristotle never released his rhetoric to the public, but rather used it in teaching as a work-in-progress. There has been speculation that his reluctance to circulate the text was due to his inability to tie the informal qualities of rhetoric into his formal conception of metaphysics (Kennedy 1980).

In this section, we will discuss the parallels between rhetoric and natural language in artificial intelligence. The problem usually found with most critical work from the human sciences and humanities is that their authors say what is wrong with artificial intelligence but don't contribute a solution or guidance. In light of the previous arguments of this text, however, this section will provide a few parallels between rhetoric and artificial intelligence to help guide new directions of research into artificial intelligence.

Do these parallels mean that rhetoric has the answers to artificial intelligence? Thankfully, no. Do they show that that rhetoric has more relevance to artificial intelligence than other fields in the humanities? Not really. But analyses such as this one from research in the humanities do show that such research directions are both proper and warranted. Because the humanities study what constitutes intelligent behavior by humans, they can serve as mentors toward developing the type of machine that can achieve artificial intelligence.

Informal System and Rhetorical Probabalities

Rhetorical discourse, unlike dialectical discourse, relies heavily on probabilities. Even Aristotle, a strong advocate of deterministic metaphysics, recognized that absolute truth is often unattainable (and often not desired) in social environments. Unlike in dialectic, where truth is an inherent feature of reality based on supposed primitive truths, truth in rhetoric relies on what a social group comes to perceive as "true." Therefore, the purpose of discourse is not to discover absolute truth but to persuade the other members in a social group that a conception of truth is probably true. We have an example of rhetorical probabilities from Plato's Phaedrus:

> Socrates: If a weak and brave man, having beaten up a strong and cowardly man, is brought into court, neither must tell the truth. The coward must claim to have been attacked by two or more, whereas the other must refute this, insisting that the two of them were alone, in order to use the argument "how could a little one like me have attacked a big one like him?" (273b4-c1)

Rhetorical arguments and pragmatic discourse as a whole, as this example shows, do not rely on absolute truth or falseness but rather relies on a sense of "maybe" that leans toward but never reaches the absolute poles.

Considering reality as paralogical (primitive, absolute truths do not exist), all aspects of human discourse can be viewed as rhetorical with a focus on probabilities. Since absolute truth is unavailable, discourse is based on the agreement of a social group that something is probably true (Rorty 1989). We can't pin down a concept and say "X is absolutely true;" rather, social groups agree that "X is probably true." Therefore, truth is a matter of social persuasion and rhetoric represents the discourse means through which social groups manufacture and agree on what will be held as true.

Quite the opposite of rhetoric-using humans, computers as dialectic, deductive machines need items synthesized into elements of absolute truth (1) and falseness (0). For this reason, even on a macro-level, the computer cannot reason in terms of probabilities; either something is absolutely true or not. Where this aspect of formal strictness causes problems is in a situation such as the Imitation Game in which the computer needs to act rhetorically through persuasion. Here, the machine is not arguing from absolute truth (it's lying), but it is attempting to persuade the humans of the probability that it is telling the truth. Such an argument is possible with rhetoric but not with dialectic.

To achieve this ability to use probabilities, an artificially intelligent machine must not be restricted to formal logic but be able to operate through informal procedures. What I mean by "informal" is that the machine needs to work within the spectrum between the absolutes instead of operating in terms of absolute (1) and (0).

Fortunately, we already have an example of an informal system generating intelligent activity, the human brain. Neurons operate by using this spectrum between the absolutes when they are excited to produce brain activities. When a neuron is stimulated and emits a signal, the signal's strength diminishes as it spreads through the dendritic trees that lead to other neurons (Stillings et al. 1987). So the brain, unlike the computer, does not act in a binary fashion because signals aren't used in ON (1) / OFF (0) ways. Rather, the entire spectrum between ON and OFF is used, due to the varying gradients of stimulus received and emitted by neurons.

Therefore, by recognizing that probabilities, not absolutes, are the basis of reasoning and discourse, we need to develop machines that operate informally within the spectrum between truth and falseness.

Categories, Frames, and Scripts

Aristotle believed that discourse could be divided into categories that were grouped according to similarities of features or purpose (1385b6). Logically, through heuristics of argument, one could use these categories to prove an argument through rational proof. But in his Rhetoric (from I Chapter 3 through II Chapter 17) he became convinced that rhetoric limited to rational proof did not describe oratory as it was practiced (Kennedy 1980). Rather, he recognized that contextual social issues would evoke responses from the audience due to associated matters outside the categories. For example, in law cases where pain was involved, a sense of pity would be naturally evoked from the jury. Often the human associations made between concepts like pain and pity played a large part in the jury's decision about what was probably true (1385b12). Depending on the hearers' experiences with something like pain, the sense of pity would be stronger or weaker.

In artificial intelligence, Minsky's concept of frames and Schank's concept of scripts is somewhat equivalent to categories and heuristics respectively. In a formal system like a computer, as in dialectic, the boundaries of the frames and scripts are strictly defined. As Minsky (1986) and Schank (1975, 1986) point out, psychologists have found that the human brain tends to work in linear schemas like scripts, grouping information into categories like frames. But something they neglect to notice is that these schemas and categories are not formally defined systems as computers require. Rather, humans have the ability to make informal, non-linear associations between seemingly unrelated members of different categories depending on an individual's experiences. These informal "associative connections" seem to operate through a parallel network that is outside of the working schemas (Stillings et al. 1987).

Through the car example of two sections ago, we can see how these meaning associations affect the use of natural language. For two people, Bob and Susan, the concepts of "car" and "truck" tend to exist in the same category which we will label "vehicle." For both of them, the concepts of "car" and "mountain" would probably fall into separate categories. But for Bob, who faithfully drives to the mountains in Colorado to ski at least once a year, the concepts of "car" and "mountain" are more strongly associated in his mind than in Susan's, who has never driven to the mountains.

Despite their different strengths of connection between "car" and "mountain," though, for both Bob and Susan the concept of "truck" probably still makes very little association with that of "mountain."

Psychologists have shown through timed experiments that these associations between categories are direct and don't require a linear trace to connect the categories. So the process isn't one in which an entire frame is called up to connect two members of different categories; rather the connection is made through parallel meaning associations between individual concepts from different categories (Stillings et al. 1987). These associations complement linear schemas (such as Schank's restaurant script) without forcing an access to an entire category.

As Minsky and Schank have shown, computers can operate linearly though formalized frames and scripts, but these meaning associations (which Aristotle found to be very important to successful discourse) are unavailable due to the formal hardware of computers.

First, the brain, through its informal structure, can access bits of associated meanings directly without working back linearly through category trees.

Second, attempting to elude the problem by making sub-categories for each meaning association ("marking" as Schank (1986) proposes) the computational needs mushroom out of reason.

Third, the binary processes of computers don't allow them to access categories in gradients depending on contextual relevance. To explain, computers can either access (1) or not access (0) a category, causing all associations to be accessed equally. In humans, associations gain strength depending on contextual relevance. Obviously, the impulse from the "mountain" category will be much stronger when Bob is driving through the mountains than when he is driving to work in Iowa.

Finally, the meaning associations need to be parallel so they can be accessible while linear scripts are being used.

Through consideration of these parallel meaning associations, we find that an informal machine that doesn't rely on formal structure is needed to achieve artificial intelligence. The categories can't be formally defined because information needs to be accessed in gradients depending on ideosyncratic relevance to a context. For this reason, parallel meaning association networks are essential to compliment the linear abilities of an artificially intelligent machine.

Enthymeme and Example, Non-monotonic Reasoning and Intentionality

The ability to make informal associations outside of the categories, as Aristotle recognized, is important for effective persuasion, but isn't available to formal syllogism (dialectic deduction). Ideally, syllogisms are built on indisputable rational proof. In social situations, however, argument never blindly follows syllogistic heuristics to derive conclusions; rather, arguers know their desired conclusion and try to find the "means of persuasion" through rhetoric to bring themselves or an audience to that conclusion (1355b26). As in a courtroom, the speaker starts with a desired conclusion ("I am innocent"), then finds the proof and associations to persuade the jury that the desired conclusion is probably true.

In artificial intelligence we find a similar case in the research into non-monotonic reasoning and intentionality. Non-monotonic reasoning is when humans go beyond strict linear patterns and "draw conclusions based on incomplete information, but these conclusions are open to revision as better information becomes available" (Nute 1984). Intensionality is the ability to set a desired goal that guides the direction of behavior. Many artificial intelligence researchers have seen these qualities as requiring induction. However, by definition, induction cannot be built on deduction, leaving the binary framework of computers without inductive abilities. Nute (1984) and Rankin (1988) reinforced this situation:

> Since Nute's conception of formal systems will validate even monotonic inference as being deductively validated, as we have seen, it follows that formal systems in which non-monotonic inferences are acceptable must be non-deductive systems, necessarily (Rankin 1988).

Aristotle had discovered the same problem with dialectic, causing him to define rhetorical discourse in terms of two informal branches, enthymeme and example:

> I call the enthymeme a rhetorical syllogism, and the example a rhetorical induction. Everyone who effects persuasion through proof does in fact use either enthymeme or examples; there is no other way (1356b4).

A major difference between the dialectical and rhetorical versions of these argument patterns is that deduction and induction are formal procedures in which one follows heuristics to arrive at a true conclusion. Enthymeme and example are informal procedures in which one starts with a desired conclusion and improves the probability of it being true through rational proof and associations.

As Rankin and Nute have pointed out, a restriction to syllogisms as in computer hardware makes the important qualities of non-monotonic reasoning and intentionality inaccessable to formally deductive machines. Rather, intelligence requires the informal qualities of reasoning evidenced by enthymeme and example in rhetoric. Furthering this point, Rankin (1988) concludes that non-monotonic reasoning "appears to be one of direct parallelism" in which strictly linear processes won't allow a machine to come to a solid conclusion without a substantial base of information.

Unlike computers, human minds have the pragmatic ability, as we've discussed, to act through parallel and linear processes simultaneously. Psychologists have known since the middle of the century that neurons tend to work in parallel groupings or "societies" in which patterns of information are stored amongst a group of neurons responsible for them (Hebb 1949, Minsky 1986). So when a concept (like "car") is experienced, the neuron group responsible for that pattern is excited. Likewise, the parallel associations (such as "mountain") are activated gradiently depending on their contextual relevance.

Therefore, based on the stimulated patterns set by previous experiences, the neuron groups would be able to determine a likely conclusion based on the scripts stored from similar situations. But these are not formal conclusions: the perceived conclusion depends on the combination of inputs from both linear patterns from the past and various ideosyncratic meaning associations with the categories involved (Stillings et al. 1989). So like an enthymeme, an expected conclusion is available though the information set is incomplete.

Here is an example to clear this concept up. Bob is now driving his car to the mountains through Nebraska. The neuron grouping in which the category of trips is stored sets the general script to lead to the destination (conclusion). With his conclusion set, he might look at the map or pull from memory the means of arriving at his destination. In addition to these linear procedures, Bob's actions are also influenced by ideosyncratic meaning associations. To Bob, the flatness of Nebraska associates with boredom, and the boredom associates with an urge to drive faster. These scripts and associations all work together to lead him to his conclusion.

Now let's move ahead in the script. Bob made it to the mountains and is driving to his favorite ski resort. Due to the context, his meaning associations change his behavior. Bob associates driving in the mountains with a sense of fear. Though not a strong impulse, it does cause him to slow down a bit.

This very crude example shows on a macro-level how the brain informally uses linear patterns with parallel meaning associations to achieve non-monotonic reasoning. By interelating informal scripts with associations, the human mind can anticipate conclusions based on the overall stimulations of patterns previously stored within neuron groups. This informal process also alleviates the problem of intentionality. When a direct pattern cannot be identified, distantly similar patterns and parallel meaning associations can combine to provide a possible conclusion subject to alteration.

However, this type of reasoning, as Rankin pointed out, is not available to formal, deductive computers whose hardware restricts them to formal linear processes. To accomplish non-monotonic reasoning and intentionality an artificially intelligent machine needs to be informal, parallel, and able to pre-determine a conclusion (which is open to change depending on context) through a combination of stimuli from neuron groups. In other words, artificially intelligent machines need to use informal procedures similar to rhetoric's use of enthymeme and example.

Self-Organization and the "Knack"

And finally, one last connection. In Plato's Gorgias, Socrates argues that proper skill in rhetoric is not teachable; rather a student gains a "knack" for rhetorical skill through practice and exposure to proper ethics. Socrates compares rhetoric to cookery in that only practice and knowledge of what is good leads to success. One just can't be taught the proper procedures and do the task as well as an expert. One must develop the "knack" (462-463).

With computers, the focus is on programming. A programmer like Schank observes an activity and formalizes that activity into a script that prescribes how the computer will act given a certain set of conditions. Therefore, the programmer is responsible for setting the pattern of the activity. And yet, as we know, often times even experts can't synthesize the exact reasoning behind their approaches to problems.

Reisbeck and Schank have developed a program JUDGE for determining sentences for convicts that highlights the problems with programming behavior (Riesbeck and Schank 1989). The program takes into consideration the crime, severity of crime, remorse shown, among other linear considerations usually used by judges to make sentencing choices. Looking over a case and extracting the information set needed to make a sentencing decision, JUDGE considers similar cases from the past and the punishments delivered, then calculates through heuristics to determine a suitable punishment for the present case.

In reality, though, judges' responsibilities of assigning punishments in cases cannot be handled through simple linear procedures. Over their years of service, experienced judges develop their skills of determining fair punishment through working within the social groups within the legal system and certainly bring more to decisions than a formal heuristic. Rather, their social environments have developed and reinforced patterns in their minds. The decisions made reflect a whole combination of schemas that they have found successful and a multitude of meaning associations that social experiences have taught them.

This concept of self-patterned experience was what Socrates probably meant with his identification of rhetoric with a "knack." A human mind isn't programmed with the proper scripts; society and reality develop and reinforce general patterns that the human mind follows. Therefore, like humans, artificially intelligent machines need to be able to discern patterns prevalent in their natural and social environments and develop their own reasoning abilities. Rosenblatt and his collegues refered to this quality as "self-organization" (Rosenblatt 1962). In terms of natural language, instead of formalizing language into parsing schemes, the machines need the ability to identify patterns in natural language on their own. As far as reasoning and discourse, the machine needs to be able to self-organize reasoning patterns based on what works in society and nature.

Our jobs as researchers is to first build such machines and expose them to reality and society. Of course as any intelligent entity would, they'll make wrong associations and follow incorrect schemas, but nature and society will always be there to right them with a more successful pattern. To avoid the problems of behaviorism, when they make an association or use a script that we cannot correct with a better pattern, we would need to alter the machines' wiring to make those patterns less accessible. As in the human brain, physical influences can lead certain concepts to be stored in general categories with a restricted ability to associate with other categories.

Conclusion

In this section, we've discussed what the parallels from rhetoric tell us about what type of machine could accomplish pragmatic natural language usage in artificial intelligence. By far this discussion isn't exhaustive and many other parallels from rhetoric certainly exist. But even this limited discussion of a few points shows how rhetoric and other established fields can serve as mentors to research in artificial intelligence. All that's required is for artificial intelligence to open its research to many of the issues that have already been addressed in other disciplines. We've found several points about what a computer can't do; but in addition, as is proper, we've also found a few properties that a machine would need to achieve artificial intelligence.

AT THE BRANCHPOINT, LOOKING TO THE FUTURE

This work is concerned with the pragmatic aspects of natural language as they relate to research in artificial intelligence. In theoretical works such as this one, to write a conclusion and imagine that this discussion has resolved anything would be improper. If anything, this work is meant to provoke new questions while building a bridge through which new avenues of research can be pursued.

In the discipline of artificial intelligence, the traditional paradigm that specifies the need for computers is breaking down somewhat. In 1986, Rumelhart and McClelland through their text Parallel Distributed Processing offered a partial revival of connectionism through the building of more advanced neural networks. In their networks, unlike Rosenblatt's, specialized expert systems are connected in parallel to act in societies when stimulus is received that they were programmed to recognize. Some researchers have held up parallel distributed processing as the approach of the future for artificial intelligence. Personally, I see it as just a step in the right direction. There is still that desire in parallel distributed processing to return to rationalism and program what the neurons are supposed to do under certain situations.

Hubert and Stuart Dreyfus (1988) wrote that with the problems of heuristic branch and the revival of the connectionist branch, artificial intelligence finds itself "back at a branchpoint." But have we really stepped back with thirty years of wasted work? Not really. We now are approaching the discipline with a wider view of the problems that need to be overcome in artificial intelligence. The path certainly has been and will continue to be harder than most of the first artificial intelligence researchers probably realized. But to imply that we haven't gone anywhere since the 1950s is incorrect.

I prefer to see artificial intelligence as looking to the future. Probably due to its own inflated claims, people expect too much from artificial intelligence when in reality the discipline is still only starting. An infant when compared to other disciplines, artificial intelligence is still just feeling its boundaries. As in any other discipline, wrong paths have been followed but not without advances in understanding.

The humanities definitely have an important role to play in the future of artificial intelligence. As disciplines concerned with what constitutes human behavior, the humanities can offer guidance toward the qualities of humanness that artificial intelligence wants its machines to possess. Artificial intelligence as a discipline needs to recognize the importance of the humanities to its work. Otherwise, it will stagnate--continually falling into the traps that the humanities have already stepped over.

This work was meant to provide a bridge between the disciplines in the hope that more bridges will follow. A great amount of research, work, and understanding still needs to be done.

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